Spatial analysis of social vulnerability to the El Niño phenomenon in Ecuador: producing an assessment of vulnerability

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Abstract

The aim of this thesis is to evaluate the practicalities of constructing a vulnerability assessment in a developing country context to shocks associated with natural hazards. The sustainable livelihoods framework is used as the basis for assessing vulnerability focused on a particular set of hazards associated with a specific event - the El Niño phenomenon in the country of Ecuador. Specifically the study applies an asset-vulnerability framework to assess household and community susceptibility and capacity to cope, and develops spatially explicit models of exposure to hazards.

Relationships between assets and well-being are analysed at the household level and the results indicate that human and financial capital assets are significant correlates with well-being outcomes. Spatial differences in asset-welfare relationships are dealt with using multilevel modelling; an approach suited to household surveys where the sample design hinders the use of more rigorous tools such as geographically weighted regression. The results of the multilevel models of assets and well-being are used to create a household susceptibility typology thus incorporating assets into more general profiles of livelihoods.

The thesis analyses census data from 1990 and 2001 and demonstrates a significant association between changes in well-being and the impacts of the 1997-98 El Niño event, but highlights deficiencies in existing assessments of exposure. As a consequence spatially explicit flood and landslide models are developed for Ecuador, are overlaid on population datasets to provide district summaries, and the sensitivity of these models analysed. Summaries of exposure are combined with the household susceptibility typology and coping capacity to produce a nationwide assessment of vulnerability to El Niño.

Finally the results are validated using a case study in coastal Ecuador which shows that exposure models underestimate local impacts and that livelihood strategies are better determinants than assets of the impacts of El Niño at the household level.

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Chapter 1 : Ecuador, Vulnerability, and the El Niño phenomenon

1.1 Background: Ecuador

Ecuador is a tropical South American country located between the latitudes of 1.5º north and 5º south and with a longitude between 75º west and 81º west[1]. It is bordered by Colombia to the north and to Peru on the east and south. The country is characterised by three distinct geographical regions: the western coastal lowlands, the highlands of the Andes range including high altitude inter-Andean valleys, and the Amazon lowlands in the east of the country (Figure 1) [2].

The land area of continental Ecuador is 276,841 km^2 (Central Intelligence Agency, 2009) and the population in 2001 was 12 million. Expenditure or consumption poverty [3] incidence in 2001 was estimated at 40% (Instituto Nacional de Estadística y Censos, 2008), and the GDP per capita in 2008 was US$1704[4]. The GINI coefficient of consumption, which measures inequality in the distribution of expenditure among all households[5], has varied between 0.57 in 1990 (Larrea and Kawachi, 2005) to a low of 0.42 in 1995 and rising again to 0.46 in 2006 (Instituto Nacional de Estadística y Censos, 2008). Despite the decrease in GINI since 1990 the values highlight the inequality in the distribution of wealth in Ecuador. There are also regional differences in consumption inequality with the Andean region consistently less equal than the coastal region while the Amazon has bigger fluctuations (Instituto Nacional de Estadística y Censos, 2008).

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[1] If the insular region of the Galapagos Islands is considered then the most westerly point is approximately 92º west

[2] In this study I concentrate on the continental portion of Ecuador and do not consider the Galapagos region

[3] Consumption poverty measures the proportion of the population who are unable to purchase a full complement of essential items

[4] In 2000 US$; purchasing power parity in 2008 US$ is estimated at US$7500

[5] A value of 0 implies perfect equality while a GINI coefficient of 1 represents perfect inequality.

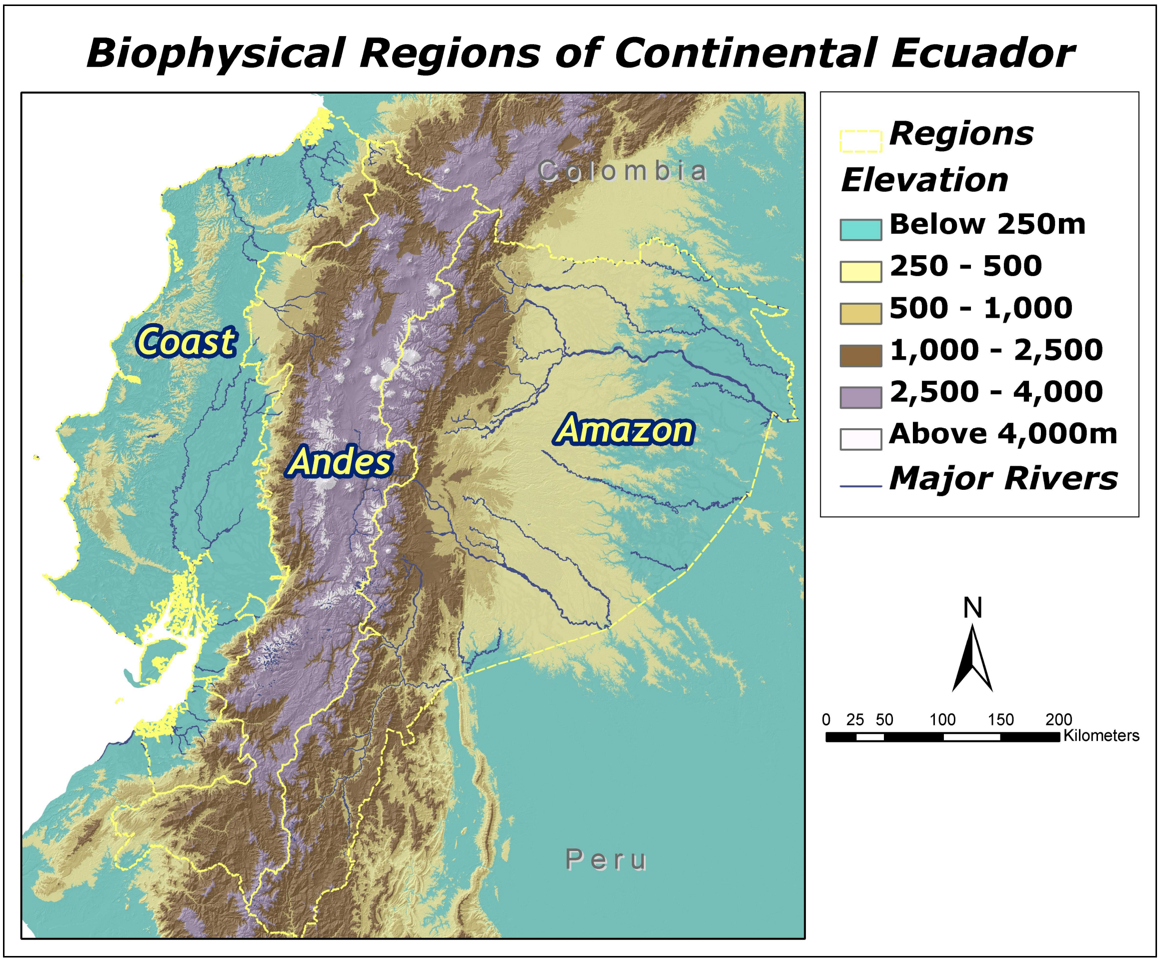
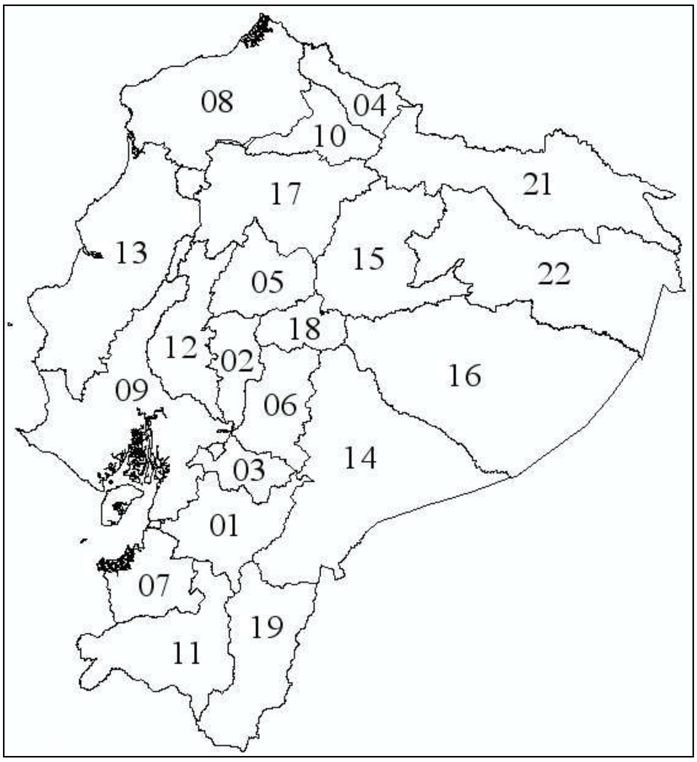


Figure 1. Topography and biophysical regions of continental Ecuador

Local government in Ecuador is organised by three layers of administration, the largest – provinces – are each divided into counties, and subsequently districts. As of 2001[6] there were 21 provinces (Figure 2), 213 counties and 987 districts[7] in continental Ecuador (EcoCiencia, 2001).

[6] The most recent date for which digital data of administrative units are publicly available is 2001.

[7] In addition there were 4 counties split into 5 districts which are disputed or semi-autonomous, these have since been incorporated into provinces. The number of provinces in Ecuador has also since risen to 24.



01 = Azuay;
02 = Bolívar;
03 = Cañar;
04 = Carchi;
05 = Cotopaxi;
06 = Chimborazo;
07 = El Oro;
08 = Esmeraldas;
09 = Guayas;
10 = Imbabura;
11 = Loja;
12 = Los Rios;
13 = Manabí;
14 = Morona Santiago;
15 = Napo;
16 = Pastaza;
17 = Pichincha;
18 = Tungurahua;
19 = Zamora Chinchipe;
21 = Sucumbios;
22 = Orellana

Figure 2. Provinces of Ecuador

In Ecuador between the years 1975 and 2000 natural hazards in the form of floods, earthquakes, droughts, volcanoes, landslides and epidemics have caused the deaths of 2,626 people, injured 1210, made 155,739 homeless and affected a total of 1,746,306 people (Centre for Research on the Epidemiology of Disasters, 2002). The El Niño event has been reported to be a direct cause of 15% of hazardous incidents in Ecuador and heavy rains (in non El Niño years) caused a further 17% of incidents which caused multiple deaths, injuries or losses to property (DesInventar, 2004). These were only the cases that have been reported due to major events which affected many people at the same time. During the same period in the Netherlands (a country with a similar population to Ecuador) natural hazards were responsible for the deaths of 20 people, injured 60, and made none homeless (Centre for Research on the Epidemiology of Disasters, 2002). Whilst taking into account the population who have died, been injured or made homeless due to other causes, it is clear that natural hazards have significant deleterious effects on the livelihoods of many Ecuadorians, and reducing the number of affected people is essential.

The purported aim of policymakers in Ecuador (Organisation of American States 1991; ODEPLAN-FAO, 2001) is to ensure that communities are functional and that individuals in those communities have sustainable livelihoods (Chambers and

Conway, 1992). Assessments of vulnerability allow for a more efficient targeting of disaster mitigation (Anderson, 1995 (cited in Heijmans, 2001)) and relief efforts (Jaspars and Shoham, 1999), productive projects (Chacaltana, 2002), dissemination of information (Golnaraghi and Kaul, 1995), and construction of policies (Chaudhuri et al., 2002) whose objective is to reduce vulnerability and improve social welfare (Corporación Andina de Fomento, 2000). Policymakers are, however, often confronted with uncertain (Hewitt, 1983) or inappropriate information on livelihoods in a particular area (Vos et al., 1999).

The purpose of this thesis is to explore the practical and theoretical issues involved with producing an assessment of vulnerability of households and communities to damages to their livelihoods as a result of natural hazards. I achieve this by constructing an assessment at the national scale of vulnerability to hazards associated with the El Niño phenomenon in Ecuador. The assessment is intended to be of immediate use for decision-makers to facilitate interventions that increase the resilience (Holling, 1973) of Ecuadorian households and sustain their livelihoods. Specifically the thesis contributes to research by the International Center for Tropical Agriculture (CIAT[8]) on poverty and food security assessments in Ecuador. Previous assessments of vulnerability by CIAT to hurricanes in Central America (Winograd, 2007; Winograd et al., 2000) were considered by the author to lack rigour in the methodology and the choice of indicators. In addition the research is a learning process that will provide recommendations for future assessments in other contexts, for other hazards, and for other disciplinary domains.

I will base this assessment on data which are publicly available such as population and housing censuses, living standards surveys, elevation models, and digital atlases. This implies that the assessment could be reproduced in other geographical settings or easily modified. Such an approach enhances the transparency of the process of assessing vulnerability (Eriksen and Kelly, 2007) and elevates the influence of such assessments on perceptions of risk and risk management (Smith, 2001).

[8] Centro Internacional de Agricultura Tropical

The remainder of this chapter is divided into two sections. The first of these is theoretical framework which reviews the components of vulnerability within the theory of sustainable livelihoods. This is followed by the conceptual framework which describes the choice of a strategy for assessing vulnerability, and the broad research design of the thesis.

1.2 Theoretical framework

1.2.1 Livelihoods and vulnerability

The sustainable livelihoods framework is a general model (Soussan et al., 2001) of the process of how households and communities[9] 'gain a living' (Chambers and Conway, 1992) to ensure that their welfare objectives are maintained over time without prejudicing the livelihoods of others. The original framework was the synthesis of various approaches of investigating farming and other livelihood systems and was concerned principally with improving development planning and interventions. The framework considered five main components: (i) a context which describes the external influences (policy, climate, culture, etc.); (ii) the resources on which a livelihood can be based; (iii) the institutions and organisations that shape the way that resources can be utilised; (iv) the strategies that are employed to sustain a livelihood; and, (v) the outcomes of the livelihood strategy (Scoones, 1998). The original framework did not consider vulnerability separately; instead it was implicit in the social sustainability of livelihoods in the face of constant stresses or acute shocks (Chambers and Conway, 1992). Subsequent adaptations to the model (e.g. Department for International Development, 2001; Ashley and Carney, 1999) replaced the simple 'context' component of the framework with the 'vulnerability context'; this includes shocks, seasonality and trends.

Vulnerability is addressed by numerous disciplines ranging from disaster management to anthropology (Alwang et al., 2001) and many studies overlap with research in livelihoods. Despite differences in methodologies a common goal in vulnerability studies and interventions is the optimisation of some well-being

[9] The model allows for higher scales – such as nations (Scoones, 1998), although it has been more common to analyse smaller units of analysis like individuals or households

function or elements thereof (Alwang et al., 2001). The well-being function represents the needs and satisfiers of individuals (Max-Neef, 1991) and may consist of outcome indicators (such as basic needs indicators, anthropometrics or household perceptions) or process indicators (such as assets, income or expenditure). It follows that households are to varying degrees ‘vulnerable’ to changes in the well-being function due to exposure to hazards, which may result in reductions in well-being to levels below a socially acceptable benchmark.

Households sense and perceive their own vulnerability to low levels of well-being and these perceptions affect decision-making processes (Smith, 2001), which determine future household well-being, even when the household is not subsequently exposed to hazards.

1.2.2 Defining vulnerability

Within the literature of vulnerability studies many terms are specific to a discipline, used indiscriminately and imprecisely, or are rendered redundant - for instance “vulnerability to insecurity” (e.g. Rakodi, 1999; Eyben, 1998). A glossary of terms, with definitions selected by the author can help in the framing of a vulnerability assessment (Box 1). The difference between some terms are small but important, for instance compare ‘risk’ and ‘hazard’, terms which are often used synonymously but where the former takes into account the probability of an event and the latter the nature of the event itself.

Box 1. Glossary of terms (OED Online, 2010; Collins English Dictionary Online, 2010)

Vulnerable – adjective – Susceptible of receiving wounds or injury
Insecure – adjective – Unsafe; exposed to danger; not firm; liable to give way, fail, or be overcome
Susceptible – adjective – Capable of taking, receiving, being affected by, or undergoing something
Resistant – adjective – Tending to resist someone or something; unyielding; not susceptible

Danger – noun – Liability or exposure to harm or injury; the condition of being exposed to the chance of evil; risk, peril
Risk – noun – The possibility of loss, injury, or other adverse or unwelcome circumstance; a chance or situation involving such a possibility
Threat – noun **-** An indication of impending evil; a strong possibility of something dangerous or unpleasant happening
Hazard – noun – A thing likely to cause injury, loss
Shock – noun – A sudden and violent effect tending to impair the stability or permanence of

something; a damaging blow

Exposure – noun – The action of uncovering or leaving without shelter or defence; unsheltered or undefended condition. Also, the action of subjecting, the state or fact of being subjected, *to* any external influence.
Stress – noun – An adverse circumstance that disturbs, or is likely to disturb, the normal physiological or psychological functioning of an individual
Damage – noun – Injury, harm; *esp.* physical injury to a thing, such as impairs its value or usefulness
Loss – noun – Diminution of one's possessions or advantages; detriment or disadvantage involved in being deprived of something, or resulting from a change of conditions; an instance of this
Injury – noun – Hurt or loss caused to or sustained by a person or thing; harm, detriment, damage

Adapt – verb – To modify, to conform to new situation/environment
Cope – verb – To manage, deal (competently) with, a situation or problem
Mitigate – verb – To lessen the trouble caused by (an evil or difficulty)
Adjust – verb – To adapt oneself *to*; to get used to

Stable – adjective – Able to maintain its place or position; presenting resistance to displacement; not easily shaken or dislodged
Resilient – adjective – Tending to resume the original shape or position after the application of force or pressure

From the glossary a general definition of vulnerability can be formed:

An object of analysis is vulnerable when it is capable of receiving damage or loss due to exposure to a hazard. The degree of vulnerability depends on the combination of the probability of exposure to a hazard, the susceptibility of the object to suffer damage or loss, and the consequences of any damage to the long-term function of the object.

Four components of vulnerability (cf. 'risk-chain' in Alwang et al., 2001) can be constructed: (i) the object of analysis and the type of damage that the object can sustain; (ii) hazards that could cause damage to the object; (iii) condition of the object that affects its likelihood of being damaged; and, (iv) the long-term ability of the object to recover from damage. These components are considered in the following sections.

1.2.3 Object of analysis

Vulnerability is studied by many disciplines and for a wide range of objects. The overlaps between these objects of analysis are often great, for instance the society is composed of individuals and the collective vulnerability of the society is likely to be related to the vulnerability of the individual. Nonetheless the type of injury that these objects can sustain requires the measurement of different outcomes. All of these outcomes depend on the condition of the object that is trying to be maintained or improved. This study will concentrate on individual and groups of human beings, more specifically the Ecuadorian household.

The household is a unit where residence and meals are shared (Chambers and Conway, 1992) and where family labour is available for production and consumption activities. The household has been described as "*the most disaggregated social system*" (Janelid, 1980, p91) where decision-making ranges from joint to authoritarian with respect to division of labour, expenditure, problem solving and allocation of resources. Households also exchange labour with neighbours, pursue common recreational activities and participate in community affairs (Janelid, 1980).

Damage to an individual human being is anything that undermines their physical or emotional health. The household however does not have a limited lifespan nor are its well-being objectives stated explicitly. Nevertheless I make the assumption[10] that households pursue a goal of improving well-being in all its aspects (sustaining livelihoods) for the current and future members of the household utilising the household's "capabilities, assets… …, and activities required for a means of living" (Carney, 1998, p4). This model of family consensus (Samuelson, 1956, cited in Lundberg, 1993) and altruistic household head behaviour has been shown to be invalid in a number of regions around the world where intra-household competition has been identified (Hart, 1992, and Udry, 1995 both cited in Elad, 1998; Sen, 1987). However, it is impractical to track consumption or income for each individual. This is especially so in farm households where income is often generated that cannot be attributed to specific individuals (Deaton, 1997).

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[10] An assumption common in farm household modelling, e.g. Kruseman et al, 1997

This study will draw strongly from the sustainable livelihoods approach to development aid. Chambers and Conway (1992) suggest a number of levels where the sustainable livelihoods approach could be applied although they use the household (hearth sharing) as the focus of their work explaining how to operationalise the concept of sustainable livelihoods[11]. The damages or losses that can be suffered by a household relate directly to the individuals who constitute the household and indirectly to the resources managed by the household (Table 1).

Table 1. Damage or losses at the household level

Damage	**Effect on household livelihood**
Death of household member (e.g. Yamano and Jayne, 2004)	Permanent loss of human capital Potential emotional damage to other members Funerary costs Changes in household composition
Incapacitation of member (e.g. Baeza and Packard, 2006)	Temporary loss of human capital Potential medical costs Potential emotional damage to other members
Loss of employment of member (e.g. Humphrey, 1994)	Temporary loss of financial capital Temporary loss of working experience/human capital
Damage or loss of physical structure, goods and services of household living space (e.g. del Ninno et al., 2001)	Reconstruction costs Costs of re-purchase Potential emotional damage to members
Damage or loss of physical structure, goods and services of household productive space (e.g. Charvériat, 2000)	Reconstruction costs Costs of re-purchase Opportunity costs of lost production

1.2.4 Hazards: potential sources of damage to Ecuadorian households

There exist many man-made and natural hazards that can cause damage to the livelihoods and thus the welfare of Ecuadorian households (Table 2). The potential of hazards to cause damage has two components, a spatial and temporal component which is the actual exposure to hazards, and a non-spatial component - the susceptibility of households or household members to damage. Some authors (e.g.

[11] See also Twigg (2007) for an example of operationalising the SL framework for disaster risk reduction

Burton et al., 1993) consider hazard to be the risk of exposure, but in this study I use the definition in Box1, and also I consider only natural hazards.

Table 2. Natural hazards with the potential to cause damages to Ecuadorian households

Hazards to members of the household that could lead to death or incapacitation	• Extreme cold or extreme heat • Lack of water or excessive loss of water • Accidental avoidable events such as drowning or falls • Natural events such as volcanic eruptions, hurricanes & earthquakes • Physical attack by animals or other human beings • Poisoning by animals or plants • Acute short-term diseases • Chronic long-term diseases • Emotional or mental stress leading to physical deterioration
Hazards to members of the household that could lead to loss of employment	• Natural events such as volcanic eruptions, hurricanes, earthquakes, drought and flood, which reduce the viability of employment
Hazards with the potential to damage household assets	• Pests and diseases • Natural events such as volcanic eruptions, hurricanes, earthquakes, drought and flood

(Calero, 2009; Burton el at, 1993)

The social risk protection literature classifies hazards (risks or shocks) as idiosyncratic or covariate according to the proportion of households affected in a particular area. When few households are exposed a hazard is said to be idiosyncratic (for example a snakebite causes the death of a member of the household), whereas when many households are affected the hazard is said to be covariate (e.g. a volcanic eruption forces a whole community to be displaced).

1.2.5 Susceptibility of Ecuadorian households to damage

The likelihood of Ecuadorian households being damaged will depend to a great extent on the exposure to hazards and the ability to resist these hazards. Table 3 outlines the hazards that threaten Ecuadorian households, the factors that determine whether households are exposed to hazards and the characteristics of households that make them more or less susceptible to damage as a result of exposure to a hazard.

Table 3. Exposure and susceptibility to natural hazards

Death or incapacitation of member		
Hazard	*Exposure*	*Susceptibility*
• Extreme cold or extreme heat	Location / occupation	Protective clothing / physical condition
• Lack of water or excessive loss of water	Location / occupation	Water provisions / physical condition
• Accidental avoidable events such as drowning or falls	Location / occupation	Physical condition / availability of medical assistance
• Natural events such as volcanic eruptions, hurricanes & earthquakes	Location / occupation	Physical condition
• Physical attack by animals or other human beings	Location / occupation	Physical condition / availability of medical assistance
• Poisoning by animals or plants	Location / occupation	Physical condition / availability of medical assistance
• Acute short-term diseases	Location / occupation / density of disease vectors / levels of contamination	Physical condition / availability of medical assistance
• Chronic long-term diseases	Family history / location / occupation / levels of contamination / diet / physical condition	Physical and emotional condition / availability of medical assistance
• Emotional or mental stress leading to physical deterioration	Decision making control / perceptions of security	Physical condition / availability of support
Loss of employment of member		
Hazard	*Exposure*	*Susceptibility*
• Natural events such as volcanic eruptions, hurricanes, earthquakes, drought and flood which reduce the viability of employment	Location / occupation / dependence on transportation of goods and services	Quality of infrastructure / position within the employment unit
• Incapacitation of member (see above)	As above	As above
Damage to household assets		
Hazard	*Exposure*	*Susceptibility*
• Pests and diseases	Location / dependence on agricultural production assets	Quality of infrastructure / level of physical and biological protection / availability of veterinary assistance / physical condition of livestock
• Natural events such as volcanic eruptions, hurricanes, earthquakes, drought and flood	Location / dependence on transportation of goods and services / dependence on agricultural production assets	Quality of infrastructure / level of physical and biological protection

1.2.6 The long term impacts of damage to households

A household that has suffered extreme damage may be able to recover quickly without the 'livelihood' being particularly affected, for instance if the household has insured against the loss of assets or if the remaining assets are sufficient to rebuild the livelihood. Conversely for another household, a small loss, for instance the loss of a cow or sewing machine, may result in the deterioration of the household's livelihood. Blaikie et al. (1994) cite an example from Winchester (1986, 1992) in which the fortunes of two households 100 metres apart followed different paths during and after a tropical storm and where access to resources – both material and information – was the key to the impact on their livelihoods.

The challenge for researchers is to be able to assess what damages or losses a household can sustain without compromising the sustainability of its livelihood. This will require an understanding of the magnitude of damage suffered and the costs of recovery with respect to the available resources of the household including social capital and the importance of emergency relief and social safety nets.

1.3 Conceptual framework

1.3.1 Strategies for measuring vulnerability in Ecuador

Measuring vulnerability to low levels of well-being is difficult, primarily because one is trying to measure something that *"is not there"* i.e. a *lack* of security that the household will not suffer damage, and consequent deterioration in well-being (Webb and Harinayaran, 1999, pg. 298). Measuring vulnerability is also difficult given the stochastic nature of exposure to hazards and our lack of understanding exactly what household characteristics determine both susceptibility and a successful recovery from exposure to hazards. To gain insight we require longitudinal studies (e.g. McPeak, 2004; Dercon et al., 2005) that plot variation of household well-being (or proxies thereof) and assets (which I assume contribute to household well-being in the long-term) with respect to exposure to hazards (both idiosyncratic and covariate). However longitudinal studies and panel data are very rarely available in developing countries, so most vulnerability assessments rely on cross-sectional surveys and inference (Kamanou and Morduch, 2002). Alternative approaches have been used to assess vulnerability of communities to natural hazards, such as Capacities and Vulnerability Analysis (Anderson and Woodrow, 1989). While these participatory approaches are often able to accurately describe vulnerabilities they require much primary data and are difficult to apply at the national scale (Cannon et al., 2003).

Households perceive *ex ante* their vulnerability to low levels of well-being. These perceptions are based on experience of past hazardous events and an instinct to protect those assets that are vital for continued household survival (Smith, 2001). Households are generally aware of which hazards they are most susceptible to, although perceptions vary within household (Mera, personal communication, 2001). Household perceptions are a very powerful source of information regarding household vulnerability but they also need to be validated against development outcomes in order to assess their predictive power. This requires the inclusion of perceptions in longitudinal household studies, which, as mentioned above, are rarely carried out in developing countries.

In the absence of panel data three broad strategies can be defined for assessing the vulnerability of households in Ecuador (Box. 2). The first strategy implies a focus on particular hazards i.e., for each hazard identify the areas or households vulnerable to a reduction in welfare, and follows from the tradition of focussing research on hazards as triggers of disasters (Blaikie et al., 1994; Burton et al., 1993). The hazard-focussed strategy is the most commonly applied and relies on *a priori* determination of hazards according to survey data (Christiaensen and Subbarao, 2001; Tesliuc and Lindert, 2000), expert opinion, or nationally collated hazard data. Outcome indicators such as expenditure can be used in combination with information on the impact of hazards in order to produce probabilities of households moving below a benchmark of future consumption.
The second strategy would focus on household profiles and would attempt to determine the types of hazard that would negatively affect the livelihood of each household. The household-focussed strategy results in an assessment that is applicable for hazards that are unexpected or rare. Swift (1989) builds on the work of Sen to construct a conceptual framework to explain the vulnerability of rural populations to famine (which implies very low levels of well-being). This framework

envisages flows between production, consumption, assets and exchange. Blaikie et al. (1994) expand on this and other frameworks to produce a model of access to resources at the household level. The Blaikie model incorporates household profiles and structures of dominance which are used to determine opportunities and constraints to income; choices of income generating activities; livelihoods; household budgets; household decisions; the outcomes of these decisions, and; feedback into the household profile. This framework has been devised to be independent of hazards, but as the authors acknowledge to be used effectively it requires access to a huge amount of data (Twigg, 2001). In order to be able to target interventions it is necessary that all the potential recipients be ranked according to the same criteria. The ranking procedure should also utilise the same type and quality of data. The Blaikie model produces many different results according to the different scenarios; these may be difficult to assemble over large areas or where the 'rules of the game' vary greatly between areas.

A third strategy would ignore both hazards and the mechanisms of vulnerability and instead monitor indicators of well-being over time. Changes in the well-being indicators are related to observable household characteristics and these relationships (which are assumed to be temporally stationary) are applied to predict future levels of the well-being indicator – i.e. vulnerability to socially unacceptable levels of well-being (Chaudhuri et al., 2002). This strategy is useful where panel data or longitudinal studies are unavailable but there are several drawbacks, notably where vulnerability is affected by *unobservable* household characteristics, and the inability to account for unpredictable hazards that affect large numbers of people in specific locations (covariate hazards).

Box 2.Examples of vulnerability assessment strategies

Hazard focussed strategy - Famine Early Warning System (FEWS) Central America (FEWS, 2002)

The current system is in its early stages and provides information for drought hazards in Central America. The vulnerability assessment is spatial and is for crops rather than households. The purpose of this assessment is to identify hotspots, areas where drought will occur and to aid in national level estimations of crop yields. In order to show famine vulnerability further interpretation is necessary, taking into account the crops actually grown, the levels of national food availability and food distribution infrastructure.

FEWS Central America presents measurements of:

- Rainfall estimates
- Start of growing season
- Water requirements satisfaction index
- Normalized difference vegetation index

The FEWS vulnerability assessment consists of maps showing the predicted situation (for instance which areas might suffer crop failure due to lack of water) as well as the difference between current situation and historical averages.

Household profiles strategy – Access to resources in Nepal (Blaikie et al., 1977)

This study simulated 667 rural Nepali households' access to resources over time for up to 20 years. Hazards were introduced to the simulation model as components of scenarios. The households were then tracked to see how their income opportunities and well-being outcomes were affected by their baseline access profile (e.g. access to land and employment), and by the introduction of different trajectories of environmental hazards and changes in the rules of social transactions.

The simulation model produced a number of vulnerability assessments. Each assessment varied according to the nature of the hazard, the timing of the hazard(s), changes in the transforming power structures and the coping strategies employed by exposed households.

By changing the rules of the game and developing hazard scenarios the household profile approach can generate assessments for many eventualities, even those considered extremely improbable, which can be used for disaster mitigation and relief efforts.

Empirical strategy – Vulnerability of low consumption in Indonesia (Chaudhuri et al., 2002)

This study aims to predict vulnerability to consumption levels below a socially acceptable poverty line. Those vulnerable to poverty will include some of the currently poor as well as those who currently do not suffer consumption deprivation. Future levels of consumption are estimated taking into account the inter-temporal and cross sectional determinants of consumption patterns at the household level.

The authors contend that volatility of consumption (represented by a mean-zero error term) varies according to some parametric relation to household characteristics. The result is that both mean estimated consumption and variance of consumption are determined according to observable household characteristics. The end result is a probability of a household suffering future consumption below a socially acceptable level.

The authors acknowledge that shocks exist but they are more interested in outcomes (in this case consumption poverty) than causes. Idiosyncratic shocks will be well modelled by this approach but the authors concur that lack of longitudinal data mean that covariate shocks such as widespread natural events, and other macro-economic effects, are not dealt with.

The purpose of the study, the data available, and the type of interventions that are envisaged will determine the choice of measurement strategy. Given my objective and the data available the strategy for measuring vulnerability to the El Niño phenomenon in Ecuador will be a combination of strategies 1 and 2. The result being the creation of indices at the household/community level based on current theory of household vulnerability. The hazard will be determined beforehand and the households will be classified as vulnerable according to the exposure to hazard, the susceptibility of the household, and the impact of potential damages on longer term household well-being. The study will use spatially explicit models of exposure to hazards as well as the sustainable livelihoods framework to assess household and community susceptibility and capacity to cope.

1.3.2 El Niño and the consequences for Ecuador

The El Niño phenomenon is a term used to describe cyclical changes in the Pacific Ocean (Cane, 1983), specifically increases in sea-surface temperature (SST) and the depth of the thermocline between approximately 140ºW and the coast of South America (approximately 80º west). These changes are closely coupled with the atmospheric Southern Oscillation which is manifest in interannual changes in air pressure differentials between locations at the surface of the Pacific Ocean (Bjerknes, 1969). Together the phenomena are named the El Niño/Southern Oscillation (ENSO) and the strength and phase of ENSO have consequences for global weather systems, with direct effects felt as far as eastern Africa (Anyamba et al., 2002). The two extremes of SST anomalies in the eastern Pacific Ocean are the El Niño phase in which temperatures are higher than normal, and the La Niña phase in which temperatures are lower than normal. Due to the coupling of the atmospheric and oceanic systems these alterations in SST result in changes in the air pressure and consequently changes in atmospheric circulation and precipitation patterns (Horel and Wallace, 1981; Rasmusson and Wallace, 1983).

The warm, El Niño, period of ENSO is associated with a thickening of the inter-tropical convergence zone in the eastern Pacific Ocean (Vuille et al., 2000) and with greater than normal precipitation in coastal Ecuador (Bendix and Bendix, 2006). The size of the positive rainfall anomaly varies according to location but is generally greater in the central and southern coastal provinces of Ecuador with anomalies in

Machala[12] up to 2000%. These increases in precipitation are not experienced in the Andean region; in contrast the eastern and north-western Ecuadorian Andes receive less than normal rainfall amounts during the peak phase of El Niño (Vuille et al., 2000).

El Niño phases of ENSO occur roughly every 4 years although within the last century this has varied from a minimum of 2 years to a maximum of 10 years (Cane, 1983), with the average frequency also changing through time (Moy et al., 2002). The most severe El Niño event of the 20th century occurred in 1997-98 (Bell and Halpert, 1998; Dirección Nacional de Defensa Civil, 2002) and was responsible for approximately 300 deaths, 5,000 homes destroyed as well as many others damaged, destruction of the transport infrastructure, crops destroyed in the field or in storage, livestock drowned or injured, as well as outbreaks of vector-borne diseases such as malaria and dengue fever as well as water-borne diseases like cholera and leptospirosis[13] (Ministerio de Salud Pública, 1998; Dirección Nacional de Defensa Civil, 2002).

It is this, the 1997/98 El Niño event, and the principal natural hazards associated with it that is the case study for which an assessment of vulnerability is developed and more general methodological insights derived.

1.3.3 Asset-vulnerability framework

The asset vulnerability framework is an approach that focuses on assets to operationalise the sustainable livelihoods framework for assessing vulnerability (Moser, 1998; Barrett, 1999; Vatsa, 2004). The asset-vulnerability framework is the interface (Figure 3) between social-scientific research on sustainable livelihoods on the one hand, and equations of risk and vulnerability – common in the disaster risk literature (Alwang et al., 2001) – on the other hand. Such equations often result from research on the development of usable assessments of vulnerability to single or multiple hazards, shocks or stressors. The equations regularly contend that vulnerability is equivalent to a function of exposure to hazards minus some other

[12] During the 1997-98 El Niño event in the southern coastal province of El Oro
[13] Leptospirosis is transmitted via contact with fluids from infected mammals

function of coping (Equation 1) (e.g. Yusuf and Francisco, 2009; Metzger and Schröter, 2006; Boardman et al., 2003; van der Veen and Logtmeijer, 2005).

$$\text{Vulnerability} = \text{exposure to hazard} - \text{capacity to cope} \qquad (1)$$

Assets are the resources which a households and communities utilise for gaining their living. Assets enable access to resources, either directly or indirectly and are an important requirement in maintaining socially acceptable levels of well-being (Swift, 1989; Sen, 1981). Assets are also what enable households to bounce-back from the impacts of shocks on livelihoods, with Moser (1998, p3) suggesting that the quantity of assets owned is directly linked to their vulnerability to negative changes in their well-being. In this sense Moser and others tackle the second component of the vulnerability equation i.e. capacity to cope.

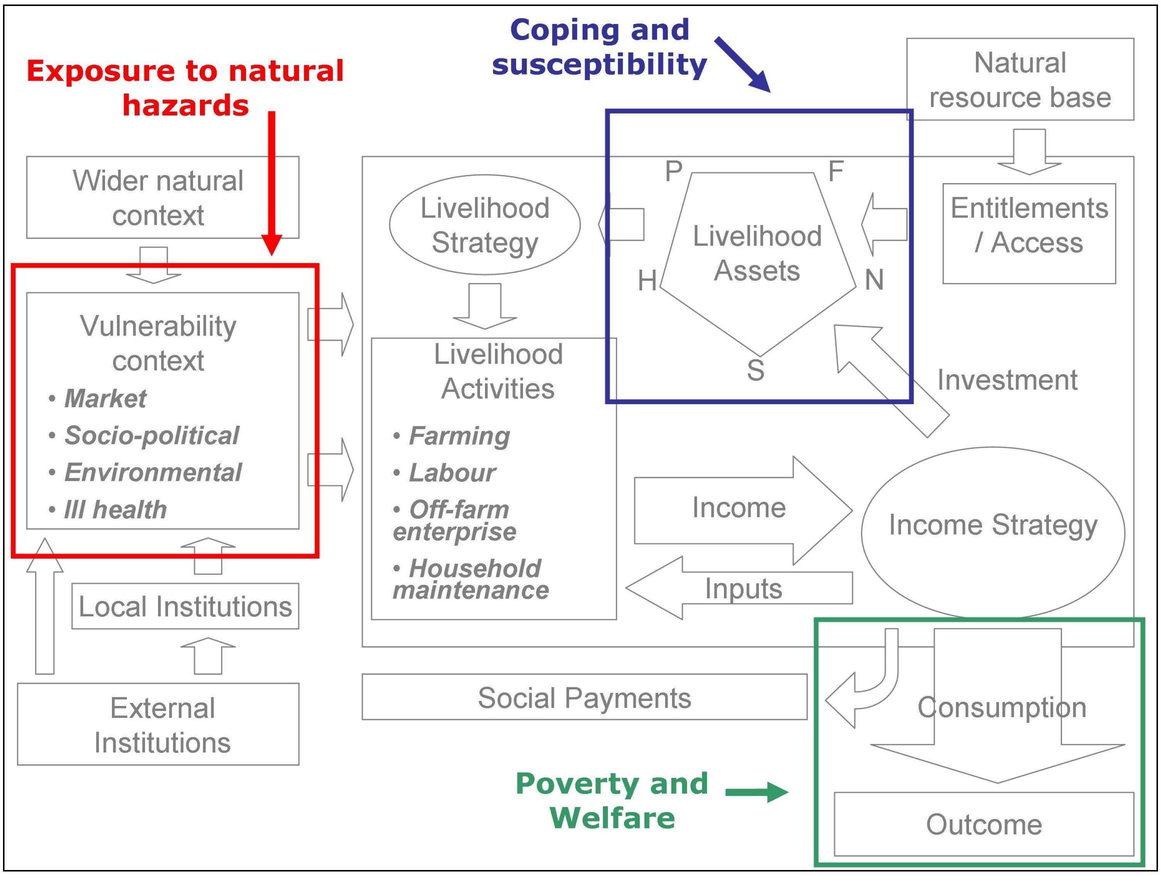

Figure 3. Interface between sustainable livelihoods framework (Soussan, 2001) and common components of vulnerability assessments

Moser identifies five categories of assets that are important for urban households: labour, human capital, productive assets, household relations and social capital. The sustainable livelihoods approach broadens household assets to include natural capital and would include labour as a livelihood activity, thus widening the scope of the asset-vulnerability framework to rural households.

Human capital is represented by skills, capabilities, knowledge, ability to work, and good health (Department for International Development, 2000). Human capital is necessary though not sufficient to ensure livelihood sustainability and increase productivity (Bratti, 2001) and investments in human capital result in significant household economic returns (Kurosaki and Khan, 2001; World Bank, 1996).

Social capital is represented by networks and connectedness, civil engagement, and relationships of trust, reciprocity and exchanges (Putnam, 1995). Social capital by nature exists at a level beyond the household although proxies that reflect the amount of social capital, such as membership of groups (Haddad and Maluccio, 2000) may be measured for individuals within households. The type of information that can be used to gauge social capital include membership of community groups, how important these groups are for the household (Buckland, 1999), how diverse the members of these groups are (Grootaert, 1999) and how democratic the decision-making process is in these groups (Grootaert, 1999). Similarly social capital is evident when members of the household trust other individuals in society (Fukuyama, 1995) and when households have reciprocal exchange arrangements with kin. A lack of social capital is associated with high levels of crime (Kawachi, 2000 cited in Restrepo, 2001).

Natural capital takes into account the direct, indirect and non-use values of natural resources. These resources include land quantity and quality, water quantity and quality, air quality, marine resources, forest resources etc. Cavendish (2000) shows that for some households ‘income’ from natural resources in Zimbabwe superseded all other forms of income.

Physical capital is the infrastructure and the equipment that allows for well-being levels and production to be maintained. Household physical capital will include private goods such as shelter, tools, etc. as well as public goods such as the provision of transport, roads, electricity, gas, telephone and communications.

Financial capital is comprised of stocks of assets such as cash, bank deposits, jewellery or flows of non-earned money such as pensions or remittances.

It can be seen that many assets are 'owned' by the household and are private goods. However a number of capitals are public goods or are accessed and managed collectively (Cavendish, 2000) or enable household assets to be utilised. This implies that livelihood domain or community characteristics have to be taken into account when attempting to describe or measure asset profiles for households.

1.3.4 Assessing vulnerability to the El Niño phenomenon in Ecuador

The research presented here will explore therefore the issues involved in applying the asset-vulnerability framework at a national level for all households in Ecuador using the 1997-98 El Niño event as a case study. The principal sources of data used in the assessment will be publicly available datasets, such as population censuses and national level household surveys. This is advantageous in the sense that it can be repeated, does not require a substantial effort in data collection, and can be conducted relatively quickly. But there is a tension between data availability and the degree to which the assessment is driven by theory (Adger and Vincent, 2005).

The research is organised in five major components (Figure 4). The first, Chapter 2 is the creation of asset profiles for households based on an econometric analysis of the contribution of particular assets to household well-being. The assets will be categorised by the five capital groups of the sustainable livelihoods framework and will include attributes of the community or livelihood domain entailing the consideration of scale issues.

Chapter 3 investigates the links between the 1997-98 El Niño event and changes in household well-being. This analysis will highlight the complexity of attributing changes in well-being (at the district level) to any particular event. The next component (Chapter 4) seeks to improve on existing models of potential exposure to hazards using spatial analysis. Extensive use is made of recently created datasets on topography and hydrological datasets in combination with high resolution models of population distribution that enable more precise measures of the number of people potentially exposed to hazards in Ecuador.

Chapter 5 presents the production of a vulnerability assessment based on an investigation of equations of vulnerability that incorporate exposure to hazards and the assets that enable households to both resist the hazards associated the El Niño phenomenon and to bounce back from damages to their livelihood (Pelling, 2003).

Chapter 6 consists of the final component, which is a validation of the results of the previous four components of the vulnerability assessment. A case study approach is used with a geographical focus on the central Ecuadorian province of Manabí.

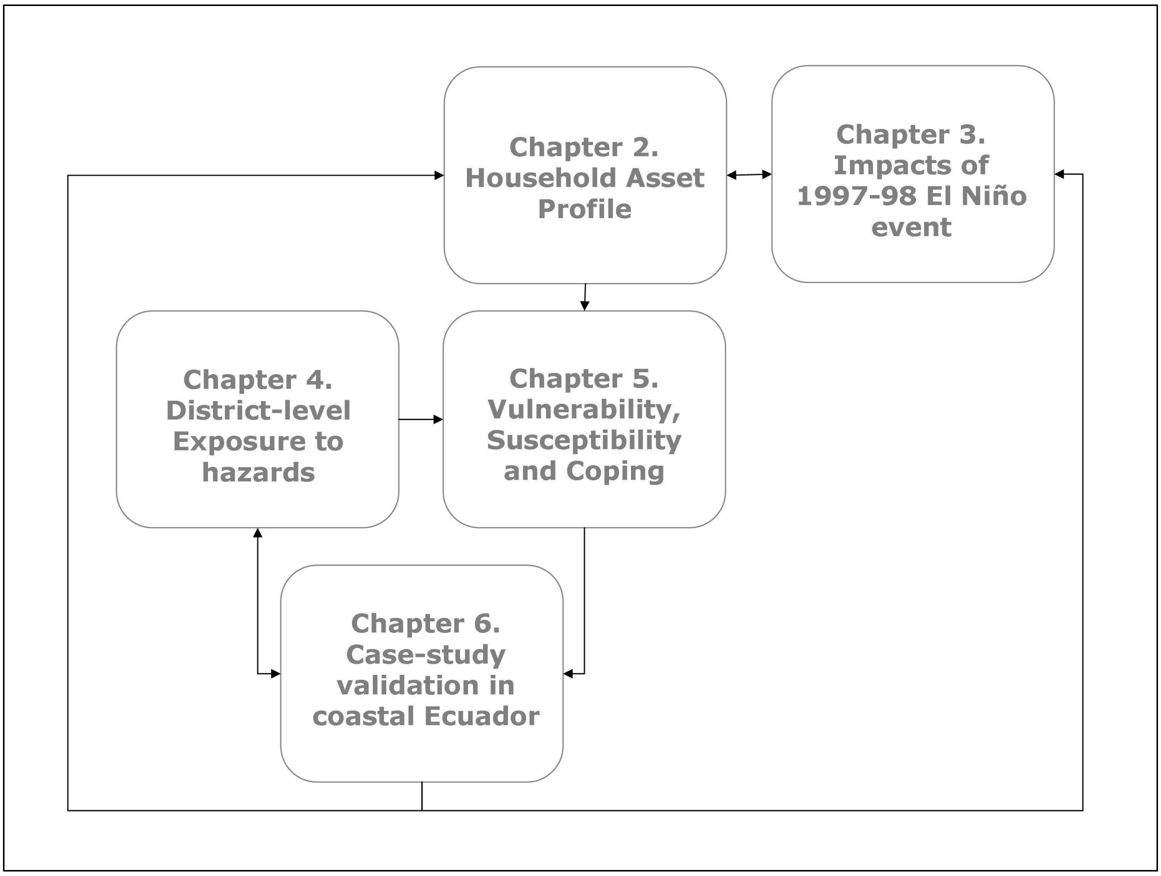

Figure 4. Research design showing main components and links between components including potential feedback loops

Chapter 7 discusses the conclusions from each component, analyses the implications of the findings in Chapter 6 on the other components, and makes recommendations for further research.

Chapter 2 : Household Asset profile

2.1 Introduction

This chapter seeks to identify which assets contribute most to household well-being in Ecuador. The purpose of understanding this link is to examine which of these assets are vulnerable to the flooding and landslides associated with the El Niño phenomenon. It will also enable the mapping of welfare before and after the 1997-98 El Niño event.

The chapter commences with a brief review of studies that investigate the links between household assets and well-being. The following section considers appropriate variables for both well-being (section 2.2.1) and assets (section 2.2.3), and the data sources available in Ecuador for the time period immediately before the 1997-98 El Niño event (section 2.2.2). The chapter continues with a section describing the modelling methodology used to investigate the link between particular assets and well-being (section 2.3). The results of the models of household well-being are shown in section 2.4 and the interpretation of the results in the context of vulnerability to natural events in Ecuador is discussed in section 2.5.

2.1.1 Links between assets and well-being

The sustainable livelihoods literature includes assets as an integral component of the livelihoods framework and there have been numerous efforts to empirically link assets to well-being. A few examples will be given here. Grootaert and Narayan (2004) investigated the relationships between assets, in particular social capital, and welfare in Bolivia. The authors hypothesise that the association of community members within groups improves information sharing, is a barrier to opportunistic behaviour, and leads to better decision-making. They also consider natural, human and physical capital explicitly in the model but exclude financial capital. The study found associations between social capital and welfare as well as significant associations between welfare and land ownership, years of education (of household head), household size, age of household head, as well as locational factors such as an urban area and the locality itself. The authors test two-way causality of group membership and welfare using “instrumental variable estimation”, choosing variables that had no effect on welfare and examined social capital in the light of these variables.

A recent study in Kenya (Kristjanson et al., 2005) analysed poverty levels at the community level and related these to assets grouped into human, physical, social, natural and financial capitals. Kristjanson et al. tested the general hypothesis that communities with higher levels of assets experienced lower levels of poverty. The authors relied on local expert opinion on assets that contribute to welfare in the region due to a lack of support from literature on empirical links between assets and poverty, and the study includes an assessment of the most important correlates of poverty amongst variables within the same asset group (e.g. natural capital assets). An important lesson from this study was that the empirical linkages between welfare and assets were often confounded by missing variables (e.g. in the social capital asset group) or by combinations of variables such as access to water and access to pasture.

Also in Kenya, Amudavi (2005) studied the effect of group participation on two indices of well-being: income, and asset ownership. In this study assets were assumed to be tangible physical assets owned by a household and the author observed positive associations between resource endowments and both income and asset ownership. Group participation was also positively linked to well-being, but only when these groups had been formed by external agencies.

2.2 Data

In order to examine the links between assets and well-being, data on both are needed. Because of the national level of investigation this study relies exclusively on secondary data sources for the analysis of household asset profiles. Bezemer and Lerman (2003) in Armenia, and Escobal and Torero (2005), in Peru, also use secondary data to investigate the role of asset complementarities in welfare. These studies use an Ordinary Least Squares regression approach (as opposed to logistic regressions in other studies). This section explores data sources in Ecuador in terms of the options for household well-being variables and the assets which are potential explanatory factors.

2.2.1 Household well-being variable

There are many potential indicators of welfare or well-being. Alkire (2002) and Lok-Dessalien (2000) present thorough reviews on the multiple dimensions of development and poverty respectively. Common indicators of well-being include: longevity (Ferriss, 2000), health status (Bourgingnon, 2001), infant or maternal mortality rates (Ferriss, 2000), nutritional intake (Bourgingnon, 2001), access to services (Martins, 2005), possessions (Lanjouw and Stern, 1991), as well as more difficult to measure perceptions of freedom (Sen, 1999; Nussbaum, 2001 cited in Anand et al., 2005) or happiness (Diener et al., 1999). The concept of indices of unsatisfied basic needs (Boltvinik, 1990) has been commonly used to measure poverty in Latin America (Feres and Mancero, 2001). These basic needs indices group together three or more basic needs, commonly access to safe water, access to housing and access to education (Feres and Mancero, 2001). The concept is similar to the Human Development Index (HDI) (United Nations Development Program, 1990) but is more applicable at the sub-national level. Within the field of household level econometrics there is a tendency to choose household level consumption (Datt and Joliffe, 1999) or income (Chaudhuri and Ravallion, 1994; Anand and Harris, 1989; Atkinson, 1989; Streeton, 1981: cited in Hentschel and Lanjouw, 1996; Amudavi, 2005) as an indicator of well-being.

Consumption is a means to an end, and often enables the satisfaction of certain basic requirements, but it may also be perceived as an end in itself. Consumption offers advantages over other well-being indicators. Consumption is more stable over time than income (Deaton, 1997); households may receive income only at certain times in the year or from a bewildering variety of sources (Hentschel and Lanjouw, 1996) which may not be well recorded by household surveys. There may also be a tendency to under-report incomes, either for tax reasons (Instituto Nacional de Estadística y Censos and Servicio Ecuatoriano de Capacitación Profesional, 1995) or if households perceive that the survey will be used to target resources.

For this study consumption is preferable to basic needs indices since the satisfaction of basic needs might include some of the physical infrastructure that form the household asset set. Basic needs may also be independent of household livelihood and may be provided by local authorities. In many locations basic services will be provided to all households that have different levels of well-being when measured with other indicators.

Household consumption is typically comprised of the following components:

- Food consumption
- Non-food consumption (such as detergents, and clothing)
- Consumer Durables (a rent value is imputed for items such as refrigerators)
- Housing (and utilities such as water, electricity or garbage collection) (a rent value is imputed)

Health and Education are often excluded from consumption aggregates because they are 'lumpy' purchases, happen at particular points in the life of the household members or may be too complex to represent. Business costs and investments in production are never included in consumption aggregates (Hentschel and Lanjouw, 1996; Deaton and Zaidi, 2001).

In order to avoid endogeneity care will need to be taken that the items used to calculate consumption are not the same assets that are used as explanatory variables.

2.2.2 Consumption data in Ecuador: 1995 *Encuesta de Condiciones de Vida*

2.2.2.1 Household consumption in the 1995 Encuesta de Condiciones de Vida

The only suitable data source for such an analysis is the 1995 *Encuesta de Condiciones de Vida* (ECV)[13]. This is based on the World Bank Living Standards Measurement Study (LSMS) surveys (Instituto Nacional de Estadística y Censos and

[13] In the 5 year period preceding the 1997-98 El Niño event two major household level socio-economic data collection exercises were undertaken: the 1994 and the 1995 ECV. The 1994 ECV need not be considered since it was superseded by the 1995 survey which had a larger sample size

World Bank, 1995) and employs a stratified sampling framework across 3 different regions and 4 areas with different urban-rural characteristics. The sampling strategy is presented in Table 4. The objective of the design and sample size of the 1995 ECV was to allow users to analyse the distinct factors that explain the different levels of living standards in society and provide information to construct household social indicators and the construction of poverty profiles. However, the sample size is insufficient to measure variables that cover small population groups or to analyse and describe socio-economic groups located in very small geographic units.

Table 4. Sample of households in the 1995 ECV

Region	Urban Area [14]	Periphery	Rural Clustered	Rural Dispersed	**Total**
Coastal	1542	37	374	611	**2564**
Andean	1410	82	263	883	**2638**
Amazon	326	36	83	163	**608**
	3278	**155**	**720**	**1657**	**5810**

The 1995 ECV has been designed to measure consumption, but does not measure subjective indicators of well-being, such as "wears good clothes" (Ravnborg, 1999, p32), or anthropometric indicators like height-for-age that would allow an assessment of nutritional outcomes. Income is captured, but for the reasons cited above it is generally more reliable to use consumption as an indicator of well-being.

Total consumption for the household includes: food and non-food items, cooking fuel, education, imputed water prices, imputed rent, and imputed consumer durable contributions (Hentschel and Lanjouw, 1996). Education was not included in the survey. These were all elicited through individual household interviews. The Ecuadorian survey adjusts the recording time period according to the type of expenditure. Therefore food items are calculated over a two-week period prior to the interview. Costs of transport and meals consumed out side the home were recorded for a one-week period. Health and hygiene products were noted for the month previous to the interview, while clothing was recorded for three months. Bigger purchases, such as consumer durables and travel, were recorded for one year prior to the interview. All these values were converted to an equivalent expenditure over two

[14] For the purposes and objectives of the ECV urban areas are considered those populated places that had at least 5000 inhabitants in their built-up sectors

weeks. All datasets were acquired from Carlos Larrea (personal communication, 5th December 2002) who worked with the World Bank in the analysis of the data and produced the first poverty maps of Ecuador (Larrea et al., 1996). The datasets included calculations for total household expenditure as well as the components of this expenditure, such as consumer durables or food items.

Total consumption is then divided by the number of household members, and further adjustments are made by the author to take into account household composition since some members of the household may be children and households may benefit from economies of scale. Household consumption is deflated using Equation 2:

$$EA = (A + \alpha K)^{\theta} \qquad (2)$$

Where EA is the number of adult equivalents in the household;
A is the number of adults in the household;
K is the number of children in the household;
α is the parameter that determines the cost of a child relative to that of an adult; and,
θ is the parameter that determines the extent of economies of scale.

Deaton and Zaidi (2001) suggest values of 0.3 and 0.9 for α and θ respectively[15]. For the purposes of this study, and following the standard used by the ECV 1995, all household members above 15 years old are classed an adult. The resulting variable has a skewness value of 4 and kurtosis value of 31.

The natural logarithm of total consumption modified by adult equivalence and economies of scale has virtually no skewness or kurtosis (0.22 and 0.21 respectively, which change to 0.25 and 0.14 when weighted by the factor of expansion[16]), and represents well the normal distribution (Figure 5). This will be the dependent variable in subsequent modelling (Table 5).

[15] Hentschel and Lanjouw (1996, p32) show that poverty profiles in Ecuador using data from the 1994 ECV are robust in the face of changing values of α and θ.

[16] The factor of expansion is used to account for the "cluster effect" which results from the 2-stage random sampling procedure. Applying the factor of expansion in analyses ensures estimates are unbiased (Grosh and Muñoz, 1996).

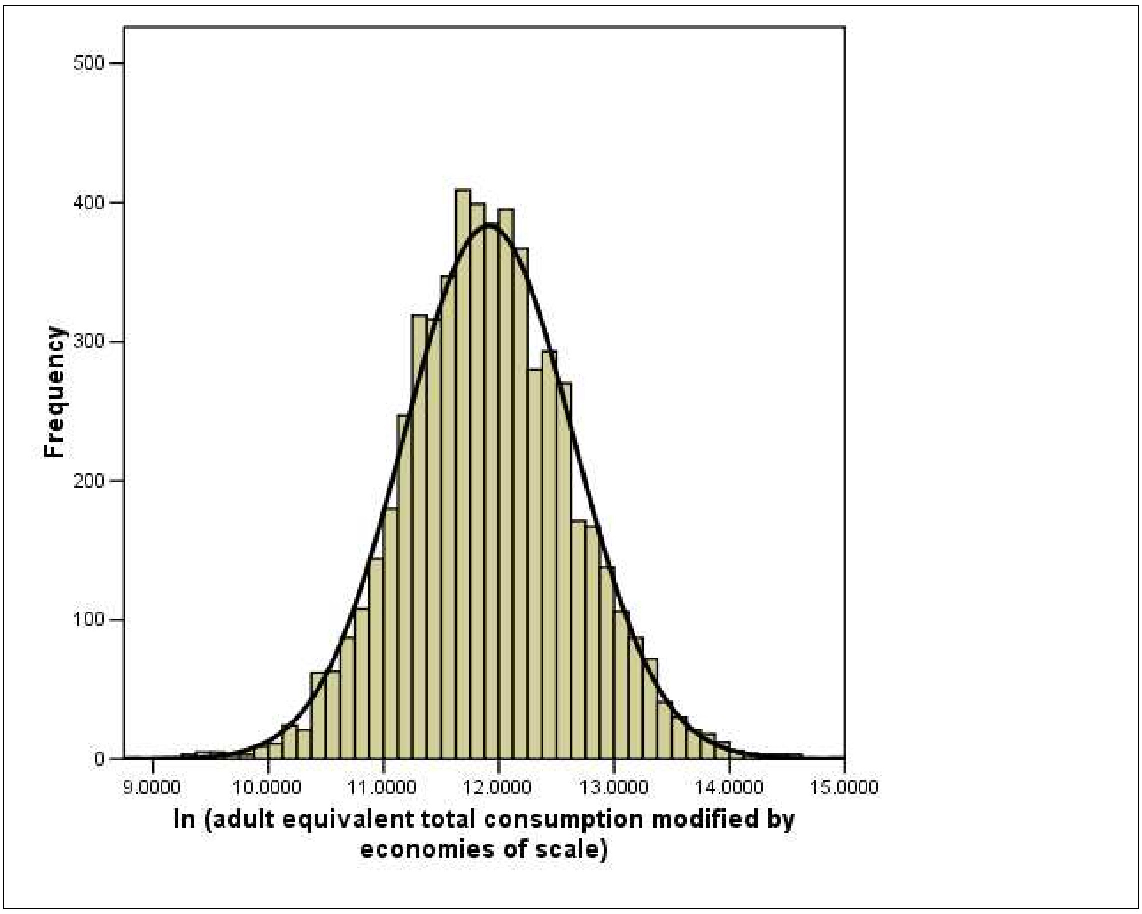

Figure 5. Distribution of household consumption per adult equivalent member, modified by economies of scale

Consumption varies between sub-groups in the ECV 1995. A comparison of means shows differences between sub-groups according to region, rural/urban area and district. The distribution of household consumption is roughly normal in all sub-groups. Only for the peri-urban households (which is a small sample) is there some negative kurtosis, and a large positive kurtosis for rural dispersed households.

Analysis of means shows that the differences between sub-groups are statistically significant when comparing between rural and urban areas but are less strong (although still significant[17]) between regions. They show that rural households have lower consumption values than urban household, and that households in the coastal region have lower values than households in the Amazon region.

[17] Using One-Way ANOVA in SPSS

These results are not surprising given the vastly different biophysical and socioeconomic environments that typify each region and the different livelihood opportunities in rural and urban areas.

2.2.2.2 District level summaries of household consumption in the 1995 Encuesta de Condiciones de Vida

Household consumption and assets will be analysed at the district as well as the household level. The analysis of household well-being at different scales is necessary due to the different contexts in which seemingly identical households are encountered. The environmental contexts as well as interaction effects between households are better captured when households are aggregated at the district level. A number of statistics can be calculated to summarise consumption when aggregated at the district level. These include the mean and the median consumption, as well as poverty indices, i.e. the relation of the consumption of each household with a predetermined poverty line. Since this study seeks to explore the contribution of different assets to well-being (consumption) levels it is appropriate to use an average (mean) value of consumption for the district level model. Individual household consumption is weighted by a factor of expansion to account for sampling biases before aggregating in each of the 55 districts sampled in the 1995 ECV.
While the choice of these districts may not capture the full range of consumption values a bigger problem of aggregation is that the distribution of mean values (Figure 6a) is far smaller than for the consumption values of all households (Figure 5). Differences in the mean values of *ln* consumption between urban and rural households are also apparent (Figure 6b & c). Mean consumption for rural households (interviewed in 31 of the 55 districts) show lower values than for urban households (interviewed in 32 of the 55 districts).

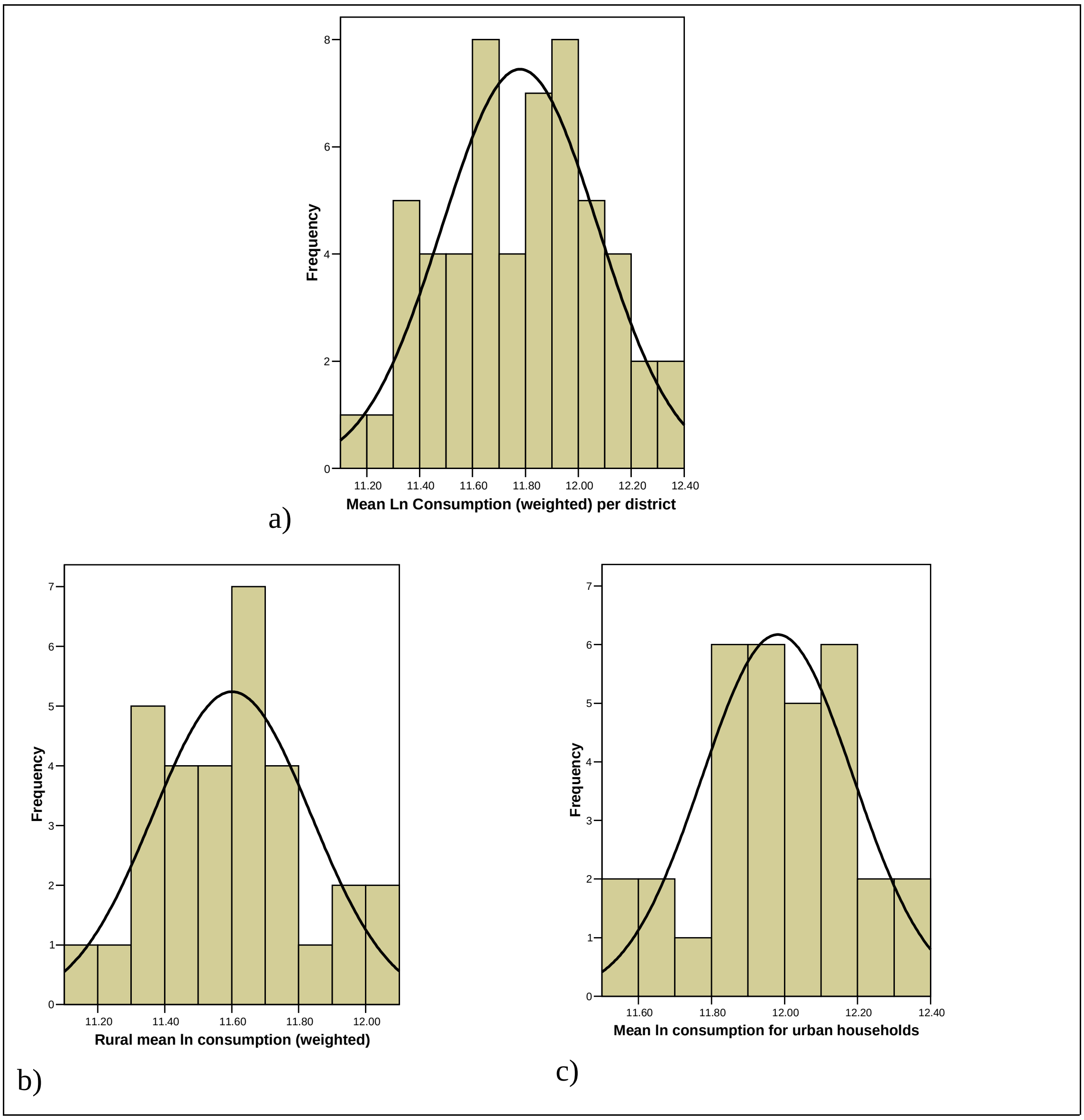

Figure 6. Distribution of aggregated household consumption per adult equivalent member modified by economies of scale and weighted for each household by an expansion factor. Histograms are shown for: a) mean *ln* consumption per household; b) mean *ln* consumption of rural households; and, c) mean *ln* consumption of urban households.

2.2.3 Explanatory variables

Explanatory variables in this analysis are assets, or proxies of assets, that contribute to household well-being. Each variable ought to have a theoretical basis for its contribution to well-being and should not be a result of well-being. Some variables, such as the education levels of the household head, will not be a result of current consumption and have a strong theoretical link to well-being. Those variables relating to the educational level of children, in contrast, will be determined in part by recent levels of household well-being.

The number of variables that are collected in the 1995 LSMS is large[18] and is compounded by the use of many dummy variables especially when these are categorical and up to seven variables are needed to capture the variation in one household characteristic (such as floor type). There are also conceptual problems of endogeneity since the household consumption aggregate includes many variables that could be considered assets.

The following sections discuss the five groups of assets considered in the sustainable livelihoods framework, namely human, social, natural, physical and financial capitals at the individual and household levels. Variables chosen for modelling at the household level are summarised in Table 5 and those at the district level are described in (Table 6).

2.2.3.1 Human capital

Human capital is the skills and experience of all members of the household that contribute to the well-being of the household. Joliffe (1997) shows that the average educational level is a better determinant of household income than the educational level of the household head alone. It can be assumed that members of the household still in full-time education are not contributing directly to household income and their educational status is likely to be correlated with current levels of well-being. Another problem with calculating an average level of education is how best to combine the different levels of education that appear in the 1995 ECV. A postgraduate education is coded as 8 but the economic returns are likely to be at least eight times greater than 'no education', which is coded as 1. A less subjective measure, and the one used in this study, is the average number of years of education for all members of the household not currently in education (H1_EDUL) (*cf.* Davis and Stampini, 2003).

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[18] There are 406 questions in the 1995 ECV many of which are subdivided into different sections. The data are split between 10 files, which vary between 120 and 360 'variables' per file.

Literacy is a key requisite to understand legal documents, such as land ownership or employment contracts or agricultural extension information. It is also important to consider which languages household members are literate in. Three commonly spoken languages in Ecuador are recorded in the 1995 ECV: Spanish, Quichua and Shuar. Literacy in Quichua or Shuar is likely to be of less value than literacy in Spanish given that Spanish is the functional language of Ecuador[19]. So household members literate only in Quichua (0.17% of literate respondents), or other languages (0.23% of literate respondents) can be discounted from the literate.
A number of authors (Green et al., 1985; Dreze and Saran, 1995, both cited in Basu et al., 2001) have shown that literacy levels of members of the household other than the household head are likely to contribute positively to household well-being. There may be problems of endogeneity in subsequent models if the literacy levels of younger household members are included, since literacy of minors may be directly related to current or recent past levels of well-being. However, literacy can have an immediate positive impact on a household so the variable used in this study is the average value of literacy in Spanish for all household members (H2_LITS).

Employment status will directly determine income levels in the household and thus consumption and well-being. Despite this there is likely to be a strong correlation with other human capital variables such as educational levels, and employment status may not be strictly considered an asset (Soussan, 2001) rather an activity (Barrett, 2001) the outcome of human capital and other assets (Figure 3). Employment can offer opportunities for an individual to increase their stock of human capital by direct training in new skills, or in the experience gained from working. Training courses are explicitly captured in the 1995 ECV, but experience from employment is more difficult to assess and there is little research on human capital acquisition in developing countries. The questions in the 1995 ECV also give little indication; respondents are not asked for how long they have been working, rather the type of work, the conditions of work, and the means of payment. The positive effect of employment on human capital accumulation will be captured, therefore, by the participation in formal training (H3_FTRN). An average will be calculated for each

[19] Bebbington and Perreault (1999) allude to the fact that indigenous leaders need to be literate in Spanish to successfully deal with institutions at higher political levels

household with a maximum of 1 (where all members have received training) and a minimum of 0.

Chakraborty and Das (2005) show that there are theoretical links in both directions between well-being (utility) and investments in human capital (health). The health of members directly affects their ability to transform human capital into other forms of capital through activities such as paid work or own-farm agriculture. Poor health also has an adverse effect on stocks of financial capital due to the costs of diagnosis and treatment but this will be treated in the section on financial capital below. Lifetime health status is not captured in the 1995 ECV, which only takes into account the health of members over the month preceding the interview. The severity of the illness or accident can be judged by whether the respondent was able to perform their normal activities. This is captured by one of the questions in the 1995 ECV. The question is directed at all members of the household regardless of age and includes studying as well as productive activities. Members of the household currently in education are assumed not to be contributing to current household well-being. Therefore the health status of all members not in education will be used to calculate the average number of days that members could not undertake their normal activities (H4_HLTH).

Human capital assets at the district level include variables such as the existence of educational and health facilities and employment opportunities. Primary and secondary schools have the potential of improving the future well-being of households by increasing the returns on investments in human capital. There are benefits to having children attending school – such as having a literate household member – but in general the presence of these facilities will not influence current levels of well-being. Other educational facilities such as technical colleges and training centres are likely to have a potential positive effect on the employment opportunities and on income. The data in the individual level questionnaire, however, makes redundant the need for these variables at the district level.

Functioning and accessible health services are obviously important in maintaining human capital assets. Where they exist they are a potentially important asset to the district. In the context of this study, however, the individual level data on health outcomes (time lost due to illnesses) negates the need to include variables on health at the district level.

Employment opportunities can be measured directly by the number of employers advertising for candidates for vacancies, or more easily by measuring the inverse – the unemployment rate – to gauge the tightness of the labour market. Once again, in this study there is access to individual level data including employment status and the search for employment.

In conclusion it appears that characteristics of the community that interact, enhance or maintain the human capital of the individual do not need to be included in a model of well-being since the individual level outcomes are already captured.

2.2.3.2 Social capital

Adger defines social capital as describing "relations of trust, reciprocity and exchange; the evolution of common rules; and the role of networks" (2003, pg 389.) Social capital can exist between household members, between households in a community, between communities in a district and can incorporate institutions and decisions at all levels. Variables of social capital are therefore dependent on the scale of analysis. At the individual level social capital has been shown to be heterogeneous, especially when measuring trust (Glaeser et al., 1999). But social capital also "resides in relationships" (Woolcock, 2001, pg69). As a result individual households within a community contribute to and benefit from community social capital to different degrees, shown empirically by Narayan and Pritchett (1999) in rural Tanzania.

Durlauf (2002) suggests that empirical studies of social capital should ensure that the definition of social capital (and thus the variables used) is causal and not functional. In this study, therefore, social capital as a household asset must support household efforts to maintain or improve levels of well-being (expenditure/income).
Typical social capital variables are poorly captured by the 1995 ECV and are at best weak proxies for social capital. Examples include the amount of time that household members have lived in their current community, financial transfers from kin and

friends, the language spoken (a proxy for ethnicity which is in itself a proxy for particular systems of reciprocity), participation in groups (workplace organisations such as trade unions, this question limited to salaried workers only) and one question on any costs in the previous year on clubs or associations. Apart from transfers from friends or family there are also questions on credit received from individuals.

The premise for including time spent in the community is the assumption that social capital increases with time (Furstenberg and Hughes, 1995 based on Coleman, 1988). It is also assumed that all members of the household accumulate social capital and as such the household value will be an average of all the members. The amount of time that an individual has spent in a community is captured by two questions, the first asks how long the respondent has been living in the current residence, a household average for this question could be biased when one member has been living in the house for many years. The alternative question asks all members over 10 years old if they were living in the same community ten years previously, and if not how long they have been living in the current location. This second question will be used in the creation of a household variable for time spent in the community. The exact number of years is not known for each individual, instead an average is calculated from the dummy variable for all members over 10 years old and not in formal education (S1_TIME) (Table 5). If all members have been in the same location for over 10 years then the average value is 1, whereas if only half the members have been in the community for 10 years the resulting value would be 0.5.

A transfer of financial capital from family or friends is an imperfect variable of social capital; it captures to some extent the bonds between individuals and levels of reciprocity between individuals. It is debateable, however, whether inter-family transfers represent social capital in the community – a household might be isolated in the community and still receive transfers from family members residing in other locations. Credit transfers also imply certain levels of trust between lender and receiver but transfers exist even where trust levels are low and other household assets are used as collateral against the loan. Given the lack of robustness of these transfer variables it is sound to exclude these from the model as part of social capital.

Ethnicity has an effect on a component of social capital that Berman (1997, cited in Krishna 2000) calls relational capital[20]. There are a number of issues, the differences between ethnic groups, does a homogeneous community have greater social capital, and does minority status lead to social exclusion and reduce social capital. Miguel and Gugerty (2005) show in western Kenya that some indicators of social capital are lower in areas where communities are mixed between different tribes, but are higher in more homogenous locations. This study refers to community level social capital but does not study the effects on minority members of the community.

Two types of social capital have been identified with respect to groups in general and which are applicable to ethnic groups. These are bonding and bridging social capital, the former stresses linkages within groups, while the latter represents so called ‘weak ties’ among members of different groups. Bonding social capital is high amongst members of Ecuador’s indigenous communities (Uquillas and van Nieuwkoop, 2003) but historically members of these communities have suffered from a political and agricultural system that favoured Spanish settlers and *mestizo* citizens (Bebbington, 1999). Ethnicity is captured in the 1995 ECV by the language spoken. Two indigenous languages – Quichua and Shuar – are recorded, and it is safe to assume that speakers of these languages are from those respective ethnic groups. Membership of a group does not necessarily confer social capital on households; this will depend on the minority/majority status of the group within the community. This information is potentially available from the 1995 ECV although samples taken from districts (*parroquias*) are representative of the domain rather than the much smaller district. Analyses of the data show that Spanish is the majority language in 54 of the 55 districts sampled. Quichua is the majority language in only one district, and even then almost 75% of respondents spoke both Spanish and Quichua. Shuar is not a majority language in any of the districts sampled but Shuar speakers account for about 10% of the respondents in one district. In the coastal region these figures are even lower and given the lack of a stronger theoretical or empirical base I will not include ethnicity as a proxy of social capital in the model.

[20] As opposed to institutional capital

At the community level social capital is often characterised by presence of groups (Buckland, 1999), collective action (Adger, 2003), the existence and enforcement of byelaws (Sanginga, 2004), adherence to taboos that seek to restrain behaviour (Stephenson, 2001), and the existence and strength of bonds between members of the community (Gittell and Vidal, 1998).

These variables are notoriously difficult to obtain unless a specific survey is conducted. Even the community level questionnaire of the 1995 ECV does not capture these variables – the most relevant variable would be the presence of a meeting room.

2.2.3.3 Natural capital

Natural capital is the soil, vegetation, animal and water resources that can be accessed by a household to sustain their livelihoods and well-being. Households may have sole access to natural capital, or these resources may be shared among members of the community or users in other more distant locations.

Access to land implies the use of natural capital for the benefit of the household. This form of natural capital is captured explicitly in the 1995 ECV. Respondents are asked if they own land, if they rent land or share land, and to what use they put this land. Landowners are also asked to give a monetary value to the land and the rent they would charge on the same land. These values imperfectly encompass the quality and quantity of land. Those who rent land are requested to give a monetary value for the rent even if they have other payment arrangements (e.g. a share of the crop or labour). An analysis of these values in the 1995 ECV shows great differences in the average value per hectare. However the mean values are skewed by outliers, which are probably due to miscoding of the land units[21]. In order to remain consistent between land owned and land rented an annual rent figure can be used to capture the natural capital of the farm (N1_LOWN & N1_LRNT) (Table 5).

Livestock are natural capital and different animals have different values for livelihoods. Kristjanson et al. (2005) used livestock density as an indicator of natural

[21] One record gives a farm with an area of 1.5 m^2 with a value of 60,000,000 sucres (or US$24,000)

capital along with NDVI (normalised difference vegetation index) values of pasture green-ness. This study was at the meso-scale and no household data were available. It was also carried out in a pastoral zone of Kenya rather than Ecuador where milk production and other rural enterprises are more common. Large animals such as cows represent greater amount of capital then smaller animals such as fowl, poultry, sheep or goats. As such four classes of animals will be used: cows (N2_LCOW), medium sized animals (sheep goats, pigs) (N3_LMED), small animals (N4_LSML), and draft and transport animals (horses, asses, mules etc.) (N5_DFT).

The majority of respondents in the 1995 ECV neither own nor rent land but rely on some components of natural capital to sustain their livelihoods. Access to water is a basic need for all households. Practically all households have access to water and nearly all practice some form of treatment. What differs between households is the time required to access water. An imputed value for water takes the opportunity cost of access to water into account and forms part of the consumption total for households. It is not, therefore, considered an asset in this study.

Both urban and rural households can have members working in agriculture. These households rely in part on the natural capital assets of others for their livelihoods. Since we do not know the employers of agricultural workers we would have to use community levels of natural capital as an indication of general levels of natural capital. Agricultural workers enters the household model and will form an interaction variable at a later stage. The ratio of agricultural workers to all workers in the household will be the variable used (N6_AGWK). I exclude in this category workers who are also owners of their own farms as well as members of the household who are not paid for their labours.

District and community level variables for natural capital will include characteristics that interact with household assets, such as the interaction between climate and land. There will also be assets that are communally owned such as forest resources or access to coastal fishing areas. There are other natural capital attributes which are utilised at the household level but for which data are not collected at that level – for instance some soil quality indicators.

In Ecuador natural capital data are available at different scales, and values are recorded for different units. Annual means of climate variables are available at a resolution of 1km. These include monthly minimum, mean and maximum temperatures as well as precipitation (Hijmans et al., 2005). Altitude is a good proxy of temperature and is available at a higher resolution of 100m (Jarvis et al., 2004). These variables are important determinants of the agro-ecology of a district but there are others that can be derived – such as the length of the growing season and its corollary the length of the dry season (NC1_DRY), which are better indicators of the natural assets available[22].

Soil quality is not easy to assess at the district level. Soil maps may show the soil type or association, but these can only give a very general idea of the constraints to agriculture, forestry or livestock activities. The scale of these maps is also generally unsuitable to assess soil quality and cannot show degradation.

Soil fertility status is also not collected for the household or farms surveyed in the 1995 ECV. An alternative is to use potential land use maps (BID-CONADE in Alianza Jatun Sacha – CDC Ecuador, 2003) and compare these with actual land use maps (compiled from various sources from the 1990's – Alianza Jatun Sacha – CDC Ecuador, 2003). Both actual and potential land use maps have been produced for Ecuador – albeit by different agencies and with different classes. A common set of categorical land use types can be defined and the two maps compared. The comparison between actual and potential land use must be guided by rules on the impact of differences on soil quality. For instance where a land use unit has the potential for agriculture but is actually afforested it may be assumed to be under-utilised, or where land is suitable for forestry but is under pasture then the land is assumed to be over-utilised and may suffer from degradation. For each class of actual land use I determine if it has been cultivated in an appropriate location given the potential of the soil. Summary statistics of productive land use suitability for each district are then produced. The result is an assessment of land use suitability (NC2_LAND) and shows areas that are not being utilised appropriately – leading to land degradation and poor soil quality.

[22] For the length of the dry-season, it is assumed that a month is dry if precipitation is less than 60 mm (Jones, personal communication). The length of the dry season is the number of consecutive months with less than 60mm.

Slope is another factor which moderates the utility of land for productive purposes. Steep slopes hinder the ability to manage the land and increase the potential for soil erosion (Pimental and Kounang, 1998). Slopes are also an integral component of the Universal Soil Loss Equation (Wischmeier and Smith, 1978). Maximum slope steepness can be derived from digital elevation models such as the Shuttle Radar Topographic Mission (SRTM) data source (Jarvis et al., 2004). These slope values can be aggregated for the whole district to give an indication of the terrain in the district (NC3_SLP).

Forest resources may or may not be accessible to the neighbouring communities. In the Amazon region of Ecuador forest resources do not seem to play a major role in the welfare of colonists from other regions (Murphy et al., 1997), but are complementary to swidden agriculture or form an integral part of the livelihoods of the indigenous population (Perrault, 2005; Nelson and Chomitz, 2006). In the coastal region of Ecuador forest resources are still exploited for timber in the province of Esmeraldas (Rudel, 2000). Use of naturally vegetated areas in other parts of the coast (which tend to be open forest and scrubby grassland) has not been documented but is likely to be locally important for firewood and other resources. Non-protected natural vegetation will therefore be considered as a potential resource for communities (NC4_NVEG) (Table 6).

2.2.3.4 Physical capital

Physical capital is tangible; assets in this category have been produced and at the household level include tools, shelter and machinery, and at the community level roads, and street lighting. Physical capital contributes to livelihoods directly or, more commonly, is used to help transform natural and human capital into financial capital.

Buildings owned and managed by the household are captured in the 1995 ECV. Housing is an asset that can be sold or rented for conversion into financial capital. Alternatively housing is an asset that helps sustain human capital (shelter), but poor quality housing can also degrade human capital, for instance overcrowding is linked to the spread of communicable diseases and certain building materials host vectors of other diseases (Abad-Franch and Aguilar, 2003).

Questions in the 1995 ECV regarding the dwelling include the type of house, as well as the material of the floors and walls. The type of house gives some indication of the value of the house, but this value will depend on a host of other factors such as the location of the dwelling, and local preferences. Similarly a hierarchy of building materials can be identified for walls and flooring but these will show variations in space and would require the use of many dummy variables since they are categorical. The number of bedrooms per person (or per adult) is considered a good indicator of overcrowding which is conducive to the spread of communicable diseases (Cardoso et al., 2004; Hodgson et al., 2001; Esteban, et al., 1998) as well as the psychological effects of having no personal space (P1_NBED) (Table 5). There may be correlation between this variable and the general health status of household members (H4_HLTH).

The value of the house is captured by a question asking the value of the dwelling if rented. Both renters and homeowners are asked this question although only owners can reap the benefits of selling the property and transforming physical capital into financial capital. This variable does not take into account other properties which are owned by the household but which are in different locations, these are assumed to be available to the household as part of financial rather than physical capital. The imputed value of rent is included in the consumption indicator for the household. Introducing the household asset as an explanatory variable will therefore introduce endogeneity into the model. This variable will be excluded.

The provision of utilities such as electricity enhances the productive potential of the household. For instance human capital can be developed if light is available to enable studying in the evening. The availability of electricity is unlikely to be a result of current levels of well-being. Actual usage levels will be dependent on well-being (indeed the quantity is included as part of the total consumption) but the variable to be measured is access to electricity (P2_ELEC).

Other forms of physical capital include tools and machinery used for agricultural production or businesses in the home. In the section in the 1995 ECV on businesses there is a question that asks what buildings, machinery or other produced goods are used in the business. A value is also given for these capital assets (P3_CPBS). However some of these businesses are not located within the household, of the 2863 households that managed some kind of enterprise only 1236 of these were located in the home. These assets are useful for the household in sustaining their livelihood and maintaining their levels of well-being and may be susceptible to damage due to a natural event. If the business is in the same district then for all intents and purposes they might as well be in the house. Unfortunately it is not possible to determine whether the businesses are in the same district but I assume that they are. Agricultural equipment (P4_CPAG) is recorded in another section of the 1995 ECV.

Physical capital at the district level relates to the infrastructure that is used to transform different capitals at the household level. Some variables are captured adequately at the household level in the 1995 ECV – such as provision of electricity. Other variables are examples of public or semi-public goods like transport infrastructure.

Jacoby (2000) has shown in a rural, developing country setting, that access to markets and services benefits the whole community, and in coastal Ecuador access depends on the road network. There are various ways of measuring the transport infrastructure at the district level. Examples include the density of the road network (Jalan and Ravallion, 2002), the quality of the road network (i.e. presence of tarmac roads) (Bryceson, 2006), and the mean accessibility to either the road network itself or a location that provides important services (Gibson and Rozelle, 2003[23]).

Data are available on both the location and the quality of the road network in Ecuador. A problem with choosing the density of the road network is that highly sinuous roads (for instance those that follow contours in mountainous landscapes) may give high density values, despite the fact that the time to move from one location to another is actually longer. Another problem is that the density measure

[23] Gibson and Rozelle used individual level responses rather than aggregates for an areal unit

will be determined by the size and extent of the district. If the density is calculated for the whole district the resulting measure may not reflect the location of the population. A large district with the population clustered in a particular quadrant or with a high urban population, for instance, may benefit from very good transport infrastructure. Jalan and Ravallion (2002) measure road density per person for an area (a Chinese county) which is an improvement and takes into account the semi-public nature of transport infrastructure. An alternative way of calculating the density would be to weight the area according to the population. This is easier to conceptualise with the mean accessibility variable. In this case the mean is calculated not on an areal basis but instead according to the accessibility of each household. This method assumes no decrease in utility even with large numbers of people. This requires information on the location of the population which is not known exactly. Indeed some population maps (Oak Ridge National Laboratory, 2002) are modified by models of accessibility to roads or towns.

Accessibility can be calculated to the road network in terms of distance. A preferable measure is time or cost to reach a destination (for buying and selling goods as well as for essential services). There is a great difference between the importance of service centres in the Andes where traditional markets have a notable social and cultural value (Martinez, Personal Communication) and the coastal region where the point of sale of agricultural produce is often the nearest road. For all services the best national measure is to use the provincial capital as the destination. Access to these locations has been calculated using CIAT's Accessibility Analyst (Farrow and Nelson, 2001), and the average value chosen for each district (PC1_ACC) (Table 6).

Other district level variables of physical infrastructure would include telephone networks – either conventional copper wire or mobile networks. Data on these are not available for these variables however.

2.2.3.5 Financial capital

Financial capital is the tangible or intangible assets that can be used as trading instruments in order to obtain other assets such as hiring labour (human capital), buying agricultural inputs (natural capital), or constructing housing (physical capital).

Current financial assets, such as savings, are not captured in the 1995 household survey, but three types of financial capital flows (apart from income) that contribute to savings or expenditure are recorded in the 1995 ECV. These are: (i) 'one-off' flows of capital (e.g. lottery winnings), (ii) irregular flows of capital without guarantees (e.g. remittances from kin, and dividends from share options), and (iii) regular flows of capital with some guarantees (e.g. government pensions). Incomes are generally thought to be a result of the livelihood activity (Figure 3) rather than an asset that contributes to the livelihood (Carney, 2002; Soussan, 2001; Ashley and Carney, 1999; Chambers and Conway, 1991). As such they will not be considered as financial capital.

Health insurance might be considered a form of financial asset since it can be used to sustain human capital. Investment in health insurance, however, can also be a result of current well-being levels rather than a determinant. Insurance schemes generally mature and provide a lump sum payment; these are obvious financial assets which may have assisted a household. Other lump-sum payments include lotteries, and gifts. Dividends from stock options are included in the 1995 ECV as lump-sum payments although they are better classified as an irregular flow. These are combined in one dummy variable (F1_LPDM) (Table 5) and the amount from all sources summed to give a value in *sucres*[24] (F2_LPSC).

Transfers from kin (or less commonly from friends) are generally considered financial capital since these transfers are independent of the livelihoods pursued by the household. Remittances are not constant and may lack the guarantees associated with pensions. There is also the possibility that the level of well-being, and poor access to livelihood choices, has caused members to migrate, who subsequently send remittances back to the household. Despite this these types of transfers will be included in the model (F3_TRDM, F4_TRSC). Rent charged on property or land is also an irregular flow without guarantees (F5_RTDM, F6_RTSC).

[24] The Sucre was the currency of Ecuador until 2001, when it was replaced by the dollar. In 1995 1US$ was equivalent to approximately 2,500sucres

Pensions from the government or private companies are a regular transfer of financial capital that is often vital to sustain household livelihoods, a dummy variable indicating the receipt of a pension is included as an asset (F7_PNDM). The monthly value of the pension(s) is also included in the household model (F8_PNSC).

Credit is another source of financial asset that can often be drawn upon to pursue or sustain a particular livelihood option. Credit differs from remittances and pensions in that it has to be paid back. The 1995 ECV asks respondents if they have received credit from institutions or individuals and if they have paid back credit during the previous 12 months. They are also asked if they have given credit, and if they have received reimbursement. In this study I will not consider payments given as credit nor given back, just whether credit has been received from individuals or institutions (F9_CRDM) and the amount (F10_CRSC).

Financial capital at the district level will include those assets that can be transformed by a local government or other agency into the infrastructure that benefits households.

Since these financial assets only benefit the household when they are transformed to other assets or transferred to the household they will not be considered in the model.

Table 5. Summary of variables to be used in the household model

Dependent Variable									**Weighted**		
			Applied to / Type	**Valid N**	**Min**	**Max**	**Mean**	**SD**	**Valid N**	**Mean**	**SD**
Y1. Natural log of total household expenditure modified by economies of scale factor			All Households Absolute	5641 (out of 5729)	8.76	14.91	11.91	0.73	2268553	11.91	0.73
									Weighted		
Explanatory variables: Assets	**Also in 1990 Census?**	**Expected relationship with household well-being**	**Applied to/ Type**	**Valid N**	**Min**	**Max**	**Mean**	**SD**	**Valid N**	**Mean**	**SD**
Human Capital											
H1_EDUL Education level (average # years in formal education)	Yes	Positive	All household members > 10 years not in formal education	15307 (out of 26941) 5562 (out of	0	9	4.3466	1.3633	2226551	4.3316	1.364

			Analytical	5758 (out of 5810))							
H2_LITS Literacy in Spanish (dummy average)	Yes	Positive	All household members > 6 years Analytical	22962 (out of 26941) 5809 (out of 5810)	0	1	0.8718	0.2362	2323459	0.8761	0.2351
H3_FTRN Formal training for employment (ratio)	No	Positive	All household members > 6 years not in formal education Analytical	1750 (out of 26941) 5758 (out of 5810)	0	1	0.1106	0.2442	2303488	0.1082	0.2399
H4_HLTH Health status (average number of days lost)	No	Negative	All household members > 6 years not in formal education Analytical	15302 (out of 26941) 5757 (out of 5758)	0	98	1.6027	4.1706	2303101	1.5617	4.1785

Social Capital											
S1_TIME In the community 10 years ago (dummy average)	Yes	Positive	All household members > 10 years and not in formal education Analytical	15084 (out of 26941) 5758 (out of 5810)	0	1	0.8194	0.3455	2303488	0.8247	0.3393
Natural Capital											
Agricultural producer – land owned	No		All households Absolute	1904 (out of 5809)							
Agricultural producer – land rented	No		All households Absolute	464 (out of 5809)							
Agricultural producer – land owned and rented (2)	No		All households Absolute	248 (out of 1891)							
N1. Agricultural	No	Positive	All	1568	20,000	5.00E+08	20207390	40295639	545342	20175690	44868894

producer– value of land owned (sucres)			households Absolute	(out of 1904 (out of 5809))							
N1_LOWN Agricultural producer – – value of land owned if rented for one year (sucres)	No	Positive	All households Absolute	1315 (out of 1904 (out of 5809))	50	1.5E+08	1705929	6205900	462303	1780656	6742314
N1_LRNT Agricultural producer – land available (value if rented)	No	Positive	All households Absolute	410 (out of 464 (out of 5809))	0	12000000	548638	1239495	162990	596909	1348974
N2_LCOW Livestock – cows owned (#)	No	Positive	All households Absolute	5809	0	400	1.7	10.4	2323315	1.37	10.3
N3_LMED Livestock –	No	Positive	All households	5810	0	95	1.5	5.0	2323850	1.41	5.2

medium animals owned (#)			Absolute								
N4_LSML Livestock – small animals owned (#)	No	Positive	All households Absolute	5809	0	807	9.9	23.8	2323524	8.9	25
N5_LDFT Livestock – draft animals owned (#)	No	Positive	All households Absolute	5810	0	40	0.37	1.3	2323850	0.31	1.28
N6_AGWK Agricultural worker/all workers (ratio)	Yes	Neutral	All household members not in formal education Structural	11038 (out of 26941) 5443 (out of 5810)	0	1	0.0862	0.2491	2172334	0.0801	0.2435
Physical Capital											
P1_NBED Number of bedrooms (#)	Yes	Positive	All households Absolute	5728 (out of 5729)	0	9	1.81	1.17	2302271	1.82	1.17

per adult equivalent											
P2_ELEC Provision of electricity to the household (dummy)	Yes	Positive	All households Absolute	5728 (out of 5729)	0	1	0.88	0.321	2302271	0.9	0.3
P3_CPBS Capital assets of businesses (sucres)	No	Positive	All households Absolute	2387 (out of 5809)	400	1210400000	13632254	50498083	966786	14525258	54885433
P4_CPAG Capital assets of agri-businesses (sucres)	No	Positive	All households Absolute	1687 (out of 5809)	0	265200000	1787134	9628838	662267	1934416	10973783
Financial Capital											
F1_LPDM Lump-sum payments in past year (dummy)	No	Positive	All households Absolute	5809 (out of 5809)	0	1	0.23	0.419	2323001	0.23	0.418

F2_LPSC Lump-sum payments in past year (sucres)	No	Positive	All households Absolute	1073 (out of 1316)	274	90000000	1880251	7293775	415461	1720823	6522040
F3_TRDM Transfers (dummy)	No	Neutral	All households Absolute	5810 (out of 5810)	0	1	0.27	0.444	2323856	0.28	0.449
F4_TRSC Transfers (sucres)	No	Positive	All households Absolute	1543 (out of 1567)	400	52800000	1612898	3496640	638710	1623226	3337281
F5_RTDM Irregular receipts from rent (dummy)	No	Positive	All households Absolute	5809 (out of 5809)	0	1	0.07	0.262	2323001	0.07	0.254
F6_RTSC Irregular receipts from rent (sucres)	No	Positive	All households Absolute	431 (out of 432)	2000	15000000	550483	1287758	161253	609884	1333235
F7_PNDM Monthly pension (dummy)	No	Positive	All household members > 10 years	5810 (out of 5810)	0	1	0.07	0.258	2323856	0.07	0.257

			Analytical								
F8_PNSC Monthly pension (sucres)	No	Positive	All household members > 10 years Analytical	412 (out of 418)	0	1703000	262393	200779	163182	260472	196237
F9_CRDM Credit received during the last year (dummy)	No	Neutral	All households Absolute	5809 (out of 5809)	0	1	0.31	0.464	2323001	0.31	0.461
F10_CRSC Credit received during the last year (sucres)	No	Positive	All households Absolute	1816 (out of 1826)	5000	100000000	4096652	9325193	705210	4071845	9839178

Table 6. Summary of variables to be used in the district level model

Dependent Variable		Valid N	Min	Max	Mean	SD
Y2. Mean value of household natural log of total household expenditure modified by economies of scale factor and weighted by factor of expansion		55	11.12	12.37	11.780	.295
Y3. Median value of household natural log of total household expenditure modified by economies of scale factor and weighted by factor of expansion		55	11.17	12.31	11.768	.291
Independent variables: Assets and context	**Expected relationship with household well-being**	**Valid N**	**Min**	**Max**	**Mean**	**SD**
NC1_DRY length of the dry season (months)	Negative	55	0	11.16	5.08	3.23
NC2_LAND land use suitability (%*10)	Positive	55	0	608.91	184.08	140.59
NC3_SLP mean slope (degrees)	Negative	55	0.79	23.86	9.80	6.57
NC4_NVEG non-protected natural vegetation (%)	Positive	55	0	9.96	3.49	2.71
PC1_ACC time to provincial capital (minutes)	Negative	55	9.04	544.45	136.52	125.26
Independent variables: Aggregated from households[25]						
HC1_EDUL Education level (average # years in formal education)	Positive	55	3.59	4.93	4.348	0.276

[25] Mean values of household variables summarised in Table 5. Each household was weighted by the factor of expansion weighting value.

HC2_LITS Literacy in Spanish (dummy average)	Positive	55	0.59	0.96	0.860	0.085
HC3_TRN Formal training for employment (ratio)	Positive	55	0.01	0.28	0.101	0.071
NC1_LOWN Agricultural producer – – value of land owned if rented for one year (sucres)	Positive	55	0	2067280	524201	506845
NC1_LRNT Agricultural producer – land available (value if rented)	Positive	55	0	360675	56968	91941
NC2_LCOW Livestock – cows owned (#)	Positive	55	0	15.47	2.118	2.825
NC3_LMED Livestock – medium animals owned (#)	Positive	55	0	20.73	1.831	2.991
NC4_LSML Livestock – small animals owned (#)	Positive	55	0.66	32.84	12.526	8.739
NC5_LDFT Livestock – draft animals owned (#)	Positive	55	0	2.01	0.449	0.518
NC6_AGWK Agricultural worker/all workers (ratio)	Neutral	55	0	0.47	0.099	0.116

2.3 Methods

2.3.1 Global Multivariate Linear Regression Models

I start by using linear regression methods to estimate a well-being function at the household level. I will analyse the coefficients in order to identify which types of household assets (Table 5) are significant determinants of well-being and whether they confirm the expected relationship between assets and well-being.

I use the reduced function in Equation (3):

$$\textit{ln}\ \text{consumption}_i = \beta X_i + \varepsilon_i \qquad (3)$$

Where X_i is the vector of characteristics for household i, which represents the household asset set.

Where ε_i is a random disturbance term

X_i = human capital + social capital + natural capital + physical capital + financial capital

I have used ordinary least squares regression to calibrate models of household well-being and aggregate household welfare for the 55 *parroquias* sampled in the 1995 LSMS. The cities of Quito and Guayaquil were over-sampled in the 1995 ECV and a factor of expansion variable is included which, when applied to the cases, remedies the over sampling in the cities. Models were run with and without weighting in order to assess the impact of weighting on the model fit.

Of the 5810 households that are surveyed in the 1995 ECV only 3872 have data for all of the variables. The implications of such a large number of missing values are manifold. Firstly the smaller sample size increases the probability that relationships between the dependent and independent variables are due to chance alone. Secondly the exclusion of certain households from the analysis may introduce bias into the analysis – for instance if the missing households happened to be located principally in rural areas, or in one region, or if certain types of households were excluded. An analysis of the missing households shows that they are from all areas and regions and include both rich and poor households. However there are more households from the coastal region excluded than would be expected from a random selection[26] and missing households tend on average to have lower consumption totals than the households included in the household model. When the explanatory variables are analysed it can be seen that literacy levels in excluded households are significantly lower than the households included in the model[27].

Skinner and Coker (1996) suggest three methods of dealing with missing variables. The first is to include only those cases with all variables; the second method is to use imputed values for variables which have many missing values, while the third uses regression models to account for complex sampling frames. These second two methods are suitable in situations where one variable is responsible for large numbers of missing cases. Of the 1938 cases with missing values approximately three quarters (1462) had only one variable with a missing value. However there was no single variable that contributed to all or even a majority of these cases. The variable with most missing values for these cases was capital invested in businesses (P3_CPBS) which accounted for 412 cases, followed by N1_LOWN, the rental value of land owned with 348 cases. Nine other variables also had missing values for these cases, the majority of which were monetary values[28]. An analysis of the variable with most overall missing values (N1_LOWN) shows that of the 590 who did not respond 298 households were able to give a sale value to their land. This suggests that lack of knowledge about the rental market was responsible for about half of the missing values while the other half is due to either an unwillingness to give any value or a

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[26] Using a χ^2 test of the three regions.

[27] Using a one-way ANOVA comparison of means

[28] Of the 1462 cases which had only one variable with missing values: P3_CPBS = 412 cases, N1_LOWN = 348 cases, N6_AGWK = 248 cases, F2_LPSC = 193 cases, H1_EDUL = 90 cases, P4_AGCP = 82, Y1 = 56 cases, N1_LRNT = 16 cases, F4_TRSC = 10 cases, F10_CRSC = 4 cases, , F8_PNSC = 2 cases, N4_LSML = 1 case

complete lack of knowledge about land prices. Imputing values for this variable using sale values of land would be possible and indeed there is a significant correlation between the two values. However imputing values for other variables is likely to be more difficult and will introduce bias (Skinner and Coker, 1996).

Another alternative is to exclude those variables which contain a large number of missing values such as P3_CPBS (total capital for businesses). The results of exclusion are not dramatic, the r^2 improves slightly to 0.294 but given that this study is more interested in the relative contributions of different capitals to household well-being the model is best left unchanged. As a result I have decided to include only those cases which have values for all variables used in the model, irrespective of the significance of each individual variable in explaining the variance in household consumption.

The global model is calibrated using the data available from 3782 households. The model explains just over 28% of the variance in the dependent variable, ln_rexpc1. The tolerance values do not suggest there are any serious collinearity issues in this model. Inspection of the eigenvectors shows some collinearity between the two variables referring to pensions, as well as between the value of land owned and the number of cows, but the condition index values are not large. When the factor of expansion is used to weight the observations the model fit slightly improves (Table 7).

2.3.2 Managing spatial non-stationarity

It is likely that there will be spatial variation in the distribution of assets. Specifically, urban areas will have less land available for crop production or grazing of livestock, but may be endowed with better public services.

It is also likely that the specific combination of assets, which are the most important for well-being, will vary spatially. Farrow et al. (2005) have shown in Ecuador that district level poverty indices and averages of household food consumption in 2001 are associated with different socioeconomic and biophysical factors according to location.

An investigation of spatial non-stationarity requires a dataset with information on both assets and well-being outcomes at a high spatial resolution, such as that used by Benson et al. (2005). The sampling framework for the 1995 ECV does not allow for the investigation of spatial non-stationarity in the relationship(s) between assets and well-being. The 1990 population and housing census, while being the most representative dataset of the 10 years previous to the 1997-98 El Niño event, does not capture household consumption (Appendix 1). The data available in Ecuador, therefore, do not allow a full exploration of the spatial variability of the relationship between household assets and well-being.

The sampling framework of the 1995 ECV allows for the creation of sub-models of the relationship between assets and well-being for urban and rural areas as well as for three regions. This method will partly compensate for potential spatial non-stationarity.

2.3.2.1 Urban-rural models

I hypothesise that there will be different models for urban and rural areas. Households in urban areas are likely to rely less on natural capital variables, with more emphasis on human capital given the wider range of employment opportunities in urban areas. Observations were selected for urban and rural areas separately and models calibrated on the selected households. For households in urban areas the variation in the dependent variable explained by the model decreases to approximately 26% (Table 7). The tolerance values do not suggest there are any serious collinearity issues in this model. Inspections of the eigenvectors suggest some collinearity between the number of animals on farm units and the value of land (which is also related to land area). The condition index values for these eigenvectors are moderately large, and there is some justification for removing some of these variables given that the sample is urban. The benefit, however, is not obvious when the model is re-calibrated, the r^2 value does not increase and the coefficients change very little. Applying weights to the urban model slightly reduces the explanatory power of the model.

When cases are selected for rural areas the r^2 values for the models are again less than the global models (Table 7). Collinearity does not seem to be a problem although the variance proportions of literacy in Spanish and average number of years of formal education are large in the same eigenvector. These two variables show significant correlation offering some justification for leaving one of the variables out of the model, however the absolute values of Pearson's r are only 0.293. I will therefore not modify the model at this point due to the strong theoretical basis for including both literacy and years of formal education. As with urban areas, applying weights does not greatly alter the adjusted r^2 of the model.

Table 7. r^2 values for global models

	Unweighted	**Weighted**
Global *(n =3872)*	0.28	0.29
Urban *(n =2215)*	0.26	0.25
Rural *(n=1657)*	0.20	0.20

It is noticeable that both the rural and urban models explain less variation than the global model. This may be due to the smaller sample size in the models or may suggest that the rural and urban sectors are not homogeneous in terms of livelihood strategies; alternatively there may be many factors idiosyncratic to households that are not captured in the model.

2.3.2.2 Regional Multivariate Linear Regression Models

In the global models it has been noted that selecting rural and urban observations does not improve the explanatory power of the household model. A possible explanation is the lack of homogeneity within these areas. A further step to account for spatial non-stationarity would be the use of regional models.

Ecuador has three distinct social and biophysical regions (excluding the Galapagos Islands) that can be used to select observations to calibrate the household model (section 1.1).

Separate models have been run to examine any differences between the three main regions. These regional models are an improvement on the global urban and rural models, in terms of the amount of variation in the dependent variable explained by the models (Table 8).

The three regions of Ecuador can also be split into urban and rural areas; however these models explain less variance than the regional models. Two interesting results are the urban Andes – which is better explained than the global urban model, and the rural Amazon, which is better explained than the global rural model. Multi collinearity is more problematic in the coastal region urban model than in the global model and less serious in the Andean region.

Table 8. r^2 values for models, observations weighted by factor of expansion

	All Areas	**Urban**	**Rural**
Global	0.29 (*n =3872)*	0.25 (*n =2215)*	0.20 (*n =1657)*
Andes	0.32 (*n =1778)*	0.29 (*n =1038)*	0.21 (*n =740)*
Coastal	0.30 (*n =1659)*	0.25 (*n =945)*	0.19 (*n =714)*
Amazon	0.29 (*n =435)*	0.24 (*n =232)*	0.27 (*n =203)*

2.3.3 Multiple-levels

It is possible that two households with seemingly identical assets may have drastically different well-being outcomes according to their location, i.e. their social, economic and environmental context.

This idea is similar to that of social contexts, common in the public health literature (Duncan et al., 1996). This study, however, treats the ‘context’ as access to commonly managed resources or as factors that interact with assets controlled by, owned by, or available to the household. These higher-level community assets range from purely private goods to purely public goods. Some assets are shared with neighbouring households in the wider community, such as the forest resources. Others – transport infrastructure for instance – facilitate the development of livelihoods and the maintenance of well-being. There are also contextual factors such as climatic conditions that interact with household assets, such as agricultural land, and alter the relationship with well-being outcomes.

Goldstein (1998) also raises the question of spatial dependency and spill over effects such that an individual is a member of many higher-level units. Thus a household is influenced by the characteristics of the district in which it is located as well as, but to a lesser distance weighted degree, by neighbouring districts.

The existence of higher-level assets, contextual factors and spatial interaction effects implies that the household model must take into account variables at levels above the household.

One strategy available to researchers is to choose household variables that already incorporate higher-level variables. Land prices, for instance, implicitly take into account the existence of markets, the quality of the land, and climatic constraints on production, and transport infrastructure. This strategy may be suitable for variables measuring monetary value but will be more difficult for other assets, such as human capital that depends on the employment context of the community in order to be transferred into production and income.

A second strategy is to model the potential determinants of household well-being separately in different models. While a third modelling strategy would include higher-level assets and contextual factors in the same model as the household variables. Given the limitations of the first strategy I have decide to concentrate on the second and third strategies.

2.3.3.1 Multiple levels in multivariate regression

In ordinary least squares multivariate regression the level of analysis is fixed and all explanatory variables are measured at the unit of analysis. If the household is the unit of analysis it is necessary to aggregate variables measured at the individual level, and disaggregate variables measured at the community or district levels (Ulimwengu and Kraybill, 2004).

Aggregation has statistical and practical implications for the model and subsequent analysis of the results. Aggregation implies a loss of information and the researcher has to be aware of the dangers of drawing inferences from aggregated data, specifically the atomistic fallacy, whereby inferences drawn regarding associations between variables at the higher level are based on observations at the individual level. The severity of the atomistic fallacy will depend on the variable in question. A rare example in the livelihoods literature is the variation of ‘access to a balanced diet’ according to income. At the individual level access is broadly dependent on income, while at the community level neighbourhoods of varying economic status have equal access to a healthy food basket (Nathoo and Shoveller, 2003). Another example is the assumption that climate is not associated with terrain at the farm scale, an assumption which does not hold at the catchment scale (Cook, et al., 2002). The corollary of the atomistic fallacy is the more common ecological fallacy (Robinson, 1950), where inferences drawn at the coarser level are assumed to hold at the individual level. This is a potential problem when data at the community level are disaggregated and the values applied to individuals. Disaggregation often results in many observations with the same values, which may artificially increase the sample size (Hox, 1995) or introduce spatial autocorrelation into a model. This is likely to be the case where data from surveys that use a clustered sample are augmented with geographical data.

2.3.3.2 District-level models

Two district level models have been calibrated for the 55 districts which were sampled as part of the 1995 ECV. The explanatory variables in the model are limited to biophysical and socio-economic factors that can be measured at the district level and which can be considered public goods or contextual factors that will affect the importance of household assets (Table 6). Variables aggregated from households in the 1995 ECV survey can be introduced into the model. This reduces the degrees of freedom in the model - a concern given the small number of cases being used to calibrate the model – but can lead to a better specified model.

The first model uses the mean values for all variables. The amount of variance explained is low (0.05) due to the limited amount of cases in the model (55). The model was re-calibrated using the median values for the dependent variable, but this model had an even lower r^2 value (0.034). A sub-model was run for the rural locations which used the mean *ln* consumption for just the rural households. This model is calibrated using only 31 cases and the model explained less than 4% of the variation. In comparison a similar model for urban households had an r^2 value of 0.13, this despite the fact that the number of cases was only 32 (Table 9).

Table 9. r^2 values for district level models

	All Areas (mean) n=55	**All Areas (median) n=55**	**Urban (mean) n=32**	**Rural (mean) n=31**
District level	0.05	0.03	0.13	0.03
District and household level variables	0.74	0.69	0.27	0.46

When household level data are entered into the model the r^2 values increase considerably, although the improvements for the model that captures urban households only is more modest. While more variance in consumption is explained there are still some fundamental problems associated with aggregating the household data as well as loss of information.

2.3.3.3 Multilevel regression models

Multilevel modelling is a response to the many studies in the social sciences where determinants of outcomes or behaviours are thought to co-exist at many scales and where obvious nesting is apparent among the objects of analysis. These studies are often based on a “multilevel problem” or a cross-level hypothesis (Hox, 1995, pg5). As a result multilevel regression models have been most commonly used in the fields of public health and epidemiology (Langford and Bentham, 1996; Duncan et al., 1996; Griffiths et al., 2004; Fotso and Kuate-Defo, 2006) and in education (Goldstein, 1987) where there are unambiguous outcomes and clear theoretical links between the outcome and possible determinants. Use of multilevel models in the empirical analysis of livelihoods, assets and well-being has been limited to psychological assessments (Kef et al., 2000). There are, however, studies that incorporate higher level biophysical variables in models of household attributes. Two studies in north-eastern Ecuador model land use at the farm level using variables from a range of scales, including the farm, community and access to services in the region (Pan and Bilsborrow, 2005; Gray et al., 2005).

Multilevel regression models do not require the aggregation or disaggregation of variables to fit the level of analysis and is generally an improvement on ordinary least squares regression (Gelman, 2004). In their simplest forms multilevel regression models are composed of separate models for each higher-level unit. The coefficients of all these variables display variance across the models; this variance is partly explained by higher-level variables.

Take the case of the household i in district j. The well-being of this household observed as consumption **Y** is a function of a matrix of some characteristics of the household **X**, while *e* is the residual error, assumed to have a mean 0 and variance σ^2.

$$\mathrm{Y}_{ij} = \beta_{0j} + \beta_{1j}\mathrm{X}_{ij} + e_{ij} \tag{4}$$

From this simple model in Equation (4) it can be seen that the intercept and slope vary for each district j. It is assumed that some district level variables will be able to explain the variance in the intercept and slope coefficients.

The slope and intercept coefficients of the model are expressed as:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\mathrm{Z}_{j} + u_{0j} \tag{5}$$

and

$$\beta_{1j} = \gamma_{10} + \gamma_{10}\mathrm{Z}_{j} + u_{1j} \tag{6}$$

Where γ_{00} is the intercept and γ_{01} is the slope coefficient, **Z** is a matrix of district level variables, and *u* is the residual error term.

I will start with a simple model with an intercept term only:

$$Y_{ij} = \gamma_{00} + u_{0j} + e_{ij} \tag{7}$$

Where Y_{ij} is the *ln* consumption for household i in district j and n = 5641.

The ‘intercept only’ model allows for the calculation of the intra-class correlation. The intra-class correlation provides a measure of the proportion of the variance at the higher-level units (such as a community or country) and the total variance. The intra-class correlation is calculated as:

$$\rho = \frac{\sigma_{u0}^2}{\sigma_{u0}^2 + \sigma_e^2} \tag{8}$$

The intra-class correlation coefficient for my well-being indicator is 0.15, where each class is a district. This shows that most variance is between individuals in a particular district rather then between districts, suggesting that the multi-level model is not as strong as I had supposed.

I have hypothesised that there are different models for rural and urban households (section 2.3.2.1) and separate models can be calibrated using these households. Splitting these models further according to the region makes little sense since the theoretical differences between regions are captured using the district-level variables.

When the sample is split into rural and urban areas (weighted according to the factor of expansion) the values for the intra-class correlations actually decrease. For the households in urban areas the intra-class correlation value is 0.07, while for rural households the value is 0.1. The sample of households surveyed in the 1995 ECV shows that some districts only contain households in urban areas or rural areas. Therefore instead of 55 districts in each model I have 32 urban districts and 31 rural districts.

Following Hox (1995) I can now add to the models the explanatory variables at the household level and assess the contribution of the variables by analysing the change in the deviance (denoted as *-2*loglikelihood* in the MlWin software [Rasbash et al., 2002]).

$$\mathrm{Y}_{\mathrm{ij}} = \gamma_{00} + \gamma_{\mathrm{P0}} X_{Pij} + u_{0j} + e_{ij} \qquad (9)$$

The difference in the deviance between the model for urban areas and the intercept only model is 6512.918 - 3623.491 = 2889.427, this value can then be tested for significance using a χ^2 test with 26 degrees of freedom. This model therefore represents a highly significant improvement over the intercept only model. When the same variables are added to the model of rural households the change in deviance again implies a highly significant improvement over the intercept-only model.
Each household level variable could have been tested individually but the objective is not to fit the best model but rather to assess the size, sign and significance of each asset.
A cursory analysis of the model outputs shows that the interpretation of the regression coefficients is difficult due to the small size of some of the γ coefficients and the fact that standardised coefficients are difficult to obtain in the MlWin software. I have decided to standardise all of the original variables used in the multi-level regression model using SPSS (SPSS, 2003) to calculate the z-scores for each variable. Files were split into urban and rural areas (although the data were standardised using all of the observations). Which are again weighted using the factor of expansion from the original 1995 ECV household level survey.

Hox (1995) suggests a next step in the exploratory multilevel analysis should be the decision to let each explanatory variable have a random as well as fixed component.

$$\mathrm{Y}_{\mathrm{ij}} = \gamma_{00} + \gamma_{\mathrm{P0}} X_{Pij} + u_{Pij} X_{Pij} + u_{0j} + e_{ij} \qquad (10)$$

When the variables in the model for urban households were allowed to have variation in the slope none of the variables caused a significant improvement in model fit (Table 10). Each variable in turn was allowed to have variation and the change in deviance was recorded. In the model for rural households, however, there was a significant improvement when three variables (tested individually) were allowed variation in their slopes. When all three variables were selected the model did not converge. The combination giving the greatest improvement of fit was P2_ELEC_Z and P3_CPBS_Z.

Table 10. Changes in deviance for multilevel model with one explanatory variable with random and fixed components

Standardised	Urban areas		Rural areas	
Variable	Deviance	δ deviance	Deviance	δ deviance
H1_EDUL_Z	3623.491	0	2960.012	0.766
H2_LITS_Z	3620.936	2.555	2960.304	0.474
H3_FTRN_Z	3623.491	0	NC	
H4_HLTH_Z	3623.491	0	2956.166	4.612
S1_TIME_Z	3623.491	0	2961.115	-0.337
N1_LOWN_Z	3623.491	0	2960.778	0
N1_LRNT_Z	3623.491	0	2960.778	0
N2_LCOW_Z	3623.491	0	2960.778	0
N3_LMED_Z	3623.491	0	NC	
N4_LSML_Z	3623.491	0	2960.778	0
N5_LDFT_Z	3623.491	0	2960.778	0
N6_AGWK_Z	3621.518	1.973	2960.778	0
P1_NBED_Z	3623.491	0	2957.182	3.596
P2_ELEC_Z	3623.491	0	2950.96	9.818**
P3_CPBS_Z	NC		2951.376	9.402**
P4_CPAG_Z	NC		2953.971	6.807*
F1_LPDM_Z	3621.610	1.881	2960.778	0
F2_LPSC_Z	NC		2960.778	0
F3_TRDM_Z	NC		2956.531	4.247
F4_TRSC_Z	NC		2956.805	3.973
F5_RTDM_Z	3623.491	0	2960.778	0
F6_RTSC_Z	3623.491	0	2960.778	0
F7_PNDM_Z	NC		2960.778	0
F8_PNSC_Z	NC		2960.778	0
F9_CRDM_Z	3623.491	0	2960.778	0
F10_CRSC_Z	3623.491	0	2960.778	0

P2 & P3	2941.915	18.863**
P2 & P4	2943.509	17.269**
P3 & P4	NC	
P2 & H4	2945.797	14.981*
P3 & H4	2947.058	13.72*
P4 & H4	NC	
P2 & F3	2947.37	13.408*
P4 & F3	2949.637	11.141*

NC = Model did not converge;* Significant at the 95% level; ** significant at the 99% level

In addition to the changes in deviance the model output allows an analysis of the covariance matrix of the variables whose slope is allowed to vary. In the case of rural households this shows that the variation in slope for the capital invested in business variable is moderately significant.

The next step is to determine how much of the random variation in the coefficients is due to explanatory factors at the district level.

$$\mathrm{Y}_{\mathrm{ij}} = \gamma_{00} + \gamma_{\mathrm{P0}} X_{Pij} + \gamma_{0q} Z_{qj} + u_{Pij} X_{Pij} + u_{0j} + e_{ij} \quad (11)$$

The incorporation of the higher level variables in the model for urban households produced a highly significant change in deviance[29], while the change for the model of rural households was more modest[30] and only significant at the 90% level (Table 12).

A final step suggested by Hox (1995) is to investigate cross-level interactions. These are relationships whereby the effect of a lower-level parameter is thought to depend substantially on the value of a higher level parameter. In my conceptual model these could be the increases in returns to well-being on investment in education, business or in agriculture depending on access to markets and services (and employment) in the first two cases, and in the numerous natural capital variables and the agro-ecological potential of the land, in the latter case.

[29] A change of deviance of 21 with the addition of 5 new variables
[30] A change of deviance of 10 with the addition of 5 new variables

In the conventional OLS regression the ratio of agricultural workers to other workers was included but it was thought that this variable could have cross-level interactions with some of the district level variables on natural capital.

Hox suggests that the cross-level interactions should be limited to those variables that showed considerable variation in their slopes, but I have decided to explore all of the possible interactions.

In the urban model a number of interactions resulted in a significant change in deviance (Table 11), many of which involved financial assets at the household level and natural assets (or contextual factors) at the district level. Two interactions were added, the first was the interaction between F5_RTDM_Z and NC1_DRY_Z (which gave the greatest improvement in fit [Table 12]) and the other was the interaction between dry months and capital invested in businesses. This second interaction was chosen because the asset group of the household level variable was physical capital rather financial.

Table 11. Interactions which significantly improve model fit

Urban areas weighted	**Rural areas weighted**
P3_CPBS_Z and NC1_DRY_Z *	P1_NBED_Z and NC3_SLP_Z *
F1_LPDM_Z and PC1_ACC_Z. *	P4_CPAG_Z and NC3_SLP_Z *
F2_LPSC_Z and NC2_LAND_Z *	F2_LPSC_Z and NC3_SLP_Z *
F4_TRSC_Z and NC2_LAND_Z *	F4_TRSC_Z and NC3_SLP_Z *
F4_TRSC_Z and NC4_NVEG_Z *	F10_CRSC_Z and NC3_SLP_Z **
F5_RTDM_Z and NC1_DRY_Z **	
F7_PNDM_Z and PC1_ACC_Z *	
F8_PNSC_Z and PC1_ACC_Z *	

* Significant at the 95% level; ** significant at the 99% level

In the rural model there is a significant decrease in the deviance when using the interaction between the mean value for the slope in the district (NC3_SLP_Z) and numerous other variables. Three interaction terms were thus added to the rural model, these were the interactions between slope and the amount of credit, a second was slope and number of bedrooms, and a third was the slope and the value of transfers, resulting in a highly significant change in deviance (Table 12).These interactions were chosen to improve the model fit and ensure that at least two asset groups from the household level variables were included.

Table 12. Improvement in model fit due to multilevel structure

Urban areas weighted		
Model	Deviance	Change
Intercept only	6512.918	n/a
Explanatory variables fixed	3623.491	2889.427***
Explanatory variables random	3623.491	0
Higher level variables	3601.073	22.418***
Interaction terms	3589.044	12.029**
Rural areas weighted		
Model	Deviance	Change
Intercept only	4910.320	n/a
Explanatory variables fixed	2960.778	1949.542***
Explanatory variables random	2941.914	18.864**
Higher level variables	2931.787	10.127
Interaction terms	2914.935	16.852***

** Significant at the 99% level***; significant at the 99.9% level

2.4 Results

2.4.1 Ordinary Least Squares regression models

This section describes the results of ordinary least squares modelling of household well-being using household level assets as the explanatory variables. Urban and rural households are modelled separately and model coefficients can be seen in Table 13 and Table 14 respectively[31]. Models are calibrated firstly using households for all parts of Ecuador and subsequently for individual regions.

[31] See Appendix 3 for full details of all models

2.4.1.1 Coefficients - urban

Educational levels (H1_EDUL) are insignificant in the model for all groups and the standardised β levels are also not high (Table 13). Literacy in Spanish (H2_LITS) shows a significant association with consumption in the global, Andean and to a lesser extent in the Amazon region but is insignificant in the Coastal region, despite the fact that literacy rates are similar in all regions. Households in all sub-groups with members receiving some form of training (H3_FTRN) seem to benefit from higher levels of consumption. Recent levels of health status (H4_HLTH) appear to have little bearing on well-being levels.

The only social capital variable (S1_TIME) - time in the community - is insignificant in all but the Andean region and the relationship with well-being is negative except for the model using urban households from the Amazon region.

The value of agricultural land (N1_LOWN) is negatively significant in the global model and in the Andean region but is insignificant in the other two regions. The value of land rented (N1_LRNT) is slightly significant in the global model but insignificant in the regional models. None of the other natural capital variables are significant apart from the number of cows (N2_LCOW) in the Amazon region. It can also be seen that increases in many of the variables are associated with lower well-being levels, this is perhaps not surprising given that only urban households are included.

The number of bedrooms per person (P1_NBED) is the variable that contributes most to household well-being. Capital invested in businesses (P3_CPBS) is highly significant in the global model and for the Andean region, less significant in the Coastal region and insignificant in the Amazon. If the business is an agricultural enterprise (P4_CPAG), however, there is no significant association with household well-being.

Table 13. Standardised β, significance levels and rankings of importance of explanatory variables in OLS models for urban areas.

		Urban Global		**Urban Andes**		**Urban Coastal**		**Urban Amazon**	
H1_EDUL	+	.010	25	.008	22	.039	16	.070	13
H2_LITS	+	.058 ***	10	.097 ***	5	.051	12	.158 **	5
H3_FTRN	+	.129 ***	3	.150 ***	3	.112 ***	4	.229 ***	3
H4_HLTH	-	-.018	23	.000	26	-.027	20	-.003	24
S1_TIME	+	**-.013**	24	**-.062 ***	9	**-.008**	24	.055	16
N1_LOWN	+	**-.103 ****	5	**-.086 ****	6	**-.106**	5	**-.158**	5
N1_LRNT	+	**-.025 ****	20	**-.003**	23	**-.066**	8	.021	20
N2_LCOW	+	.094	6	.024	19	.030	18	.314 *	1
N3_LMED	+	**-.028**	19	**-.045**	14	.007	25	**-.002**	25
N4_LSML	+	**-.050**	13	.003	23	**-.048**	14	**-.041**	19
N5_LDFT	+	**-.009**	26	.032	17	.056	10	**-.202**	4
N6_AGWK		-.031	17	-.047	12	-.009	23	-.056	15
P1_NBED	+	.299 ***	1	.307 ***	1	.300 ***	1	.244 ***	2
P2_ELEC	+	.025	20	.052	10	.004	26		26
P3_CPBS		.107 ***	4	.152 ***	2	.080 **	7	.009	23
P4_CPAG	+	.033	15	.009	21	.023	21	.156	7
F1_LPDM	+	.157 ***	2	.126 ***	4	.170 ***	2	.107	9
F2_LPSC	+	.031 *	17	.021	20	.063 *	9	**-.014**	22
F3_TRDM		-.058 **	10	-.033	16	-.094 **	6	-.044	18
F4_TRSC	+	.041	14	.041	15	.028	19	.099	10
F5_RTDM	+	**-.022**	22	.001	25	.032	17	**-.099**	10
F6_RTSC	+	.068 **	9	.051	11	.047	15	.091	12
F7_PNDM	+	**-.069 ***	8	**-.069**	8	**-.050**	13	.068	14
F8_PNSC	+	.055	12	.032	17	.056	10	**-.017 ***	21
F9_CRDM		.078 ***	7	.046	13	.145 ***	3	.132	8
F10_CRSC	+	.033	15	.075 ***	7	.020	22	.053	17

* Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9% level

Figures in **bold** type indicate parameters with a sign different to that expected. Rankings shaded green are the 5 largest standardised coefficients.

Moving on to financial capital variables it can be seen that households receiving a lump sum payment (F1_LPDM) are positively associated with higher consumption levels, this is significant in the global, Andean and Coastal models but not in the Amazon. The size of the lump sum payment (F2_LPSC) is only slightly significant. Households receiving transfers from other sources (F3_TRDM) have lower well-being levels than other households. This relationship is moderately significant in the global model and the Coastal model. The amount of rent received (F6_RTSC) is positively moderately significant in the global model but insignificant in the regional models. Pensions (F7_PNDM) are negatively associated with consumption in the national model but are insignificant in the regional models. Households receiving credit (F9_CRDM) are positively associated with higher levels of consumption in all models; this association is highly significant in the Coastal region. The amount of credit (F10_CRSC) is also significant in the Andean region but not so in the other models.

2.4.1.2 Coefficients - rural

As with urban areas the number of years in formal education (H1_EDUL) is a not a significant factor in household well-being, indeed, in rural areas of the Coastal and Andean regions the relationship is negative (Table 14). Literacy in Spanish (H2_LITS) is significant in the global and Andean model but less significant in the Coastal, and not significant in the Amazon region. Training (H3_FTRN) is highly significant in the global model, less significant in the Andes and Coastal regions, and insignificant in the Amazon region. Health status (H4_HLTH) again shows no association with household well-being, but in three of the four models as health status deteriorates well-being increases.

Time spent in the community (S1_TIME) is negatively significant in the global and Andean models but insignificant in the coastal and Amazon regions.

The value of land (N1_LOWN) is moderately significant in the global model but insignificant in the regional models. Owning animals does not contribute to household welfare and in over half the models is associated with lower well-being levels. In the Andean region the number of small animals (N4_LSML) is negatively associated with consumption, in the Coastal region the number of cows (N2_LCOW) is negatively associated with consumption; in the Amazon model animals are insignificant, while in the global model horses (N5_LDFT) are negatively associated with consumption. The mean proportion of household workers as agricultural labourers (N6_AGWK) is a highly significant variable in the global and Andean models and moderately significant in the Amazon region but the association is negative.

Once more the number of bedrooms per person (P1_NBED) is the variable that adds most to household well-being. The provision of electricity (P2_ELEC) is not a significant contributor to consumption and in three of the models the relationship is not positive. Capital invested in businesses (P3_CPBS) is positively significant in the global and coastal regions but insignificant in the other regions. As in urban areas the variable for investments in agro-enterprises (P4_CPAG) is neither significant nor a major contributor to well-being levels.

In financial capital the dummy variable for lump-sum financial gains (F1_LPDM) is positively significant in all models except the Amazon region. The dummy variable for more regular transfers (F3_TRDM) is negatively associated with consumption in all the models, but the amount of the transfer (F4_TRSC) is positively associated with consumption. This is significant in both the global and coastal models. Rent received (F5_RTDM) is only significant in the Amazon regional model where a payment is associated with households with lower well-being levels. The cash value of rent (F6_RTSC) is insignificant in all models. Receiving credit (F9_CRDM) is positively associated with consumption in the global and coastal models and insignificant in the other models.

Table 14. Standardised β, significance levels and rankings of importance of explanatory variables in OLS models for rural areas.

		Rural Global		Rural Andes		Rural Coastal		Rural Amazon	
H1_EDUL	+	**-.027**	18	**-.004**	24	**-.039**	15	.027	24
H2_LITS	+	.112***	3	.140 ***	3	.107 **	7	.059	14
H3_FTRN	+	.103***	5	.102 **	7	.115 **	6	.032	22
H4_HLTH	-	**.034**	15	**.042**	15	**.032**	18	-.091	10
S1_TIME	+	**-.088*** **	6	**-.151 *** **	2	**-.023**	22	**-.100**	7
N1_LOWN	+	.071**	11	.049	12	.063	10	.107	6
N1_LRNT	+	.005	25	.017	23	.023	22	**-.035**	20
N2_LCOW	+	.015	21	.065	9	**-.052**	11	**-.071**	13
N3_LMED	+	**-.002**	26	**-.028**	21	.044	13	.035	20
N4_LSML	+	**-.050***	13	**-.041**	16	**-.052**	11	**-.094**	8
N5_LDFT	+	**-.071****	11	**-.046**	14	**-.075**	9	**-.092**	9
N6_AGWK		-.088***	6	-.129 ***	4	-.037	16	-.180 **	3
P1_NBED	+	.239***	1	.225 ***	1	.210 ***	1	.423 ***	1
P2_ELEC	+	**-.046**	14	**-.036**	18	**-.041**	14	.047	17
P3_CPBS		.072**	10	.031	20	.132 ***	2	.029	23
P4_CPAG	+	.030	17	.035	19	.001	25	.091	10
F1_LPDM	+	.126***	2	.119 **	5	.130 ***	3	.043	19
F2_LPSC	+	.018	20	**-.004**	24	.027	20	.113	5
F3_TRDM		-.110***	4	-.060	10	-.124 **	5	-.075	12
F4_TRSC	+	.084**	8	.021	22	.130 ***	3	.011	26
F5_RTDM	+	.012	22	.040	17	.025	21	**-.283 ****	2
F6_RTSC	+	.021	19	.004	24	.017	24	.148	4
F7_PNDM	+	**-.032**	16	**-.114 ***	6	.034	17	.045	18
F8_PNSC	+	.011	24	.054	11	**-.030**	19	.020	25
F9_CRDM		.081**	9	.048	13	.080 *	8	.051	16
F10_CRSC	+	.012	22	.081 *	8	.001	25	**-.054**	15

* Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9% level

Figures in **bold** type indicate parameters with a sign different to that expected. Rankings shaded green are the 5 largest standardised coefficients.

2.4.2 Two way causality

There are a number of variables which have a theoretical causative relationship with household well-being. For instance the number of bedrooms has been shown to improve household well-being by reducing overcrowding and thus the incidence of diseases. However the number of bedrooms per person can also be seen as part of the consumption of the household, especially as an imputed figure of the rental value of the household is a component of consumption. Increased levels of well-being can also affect the choices that households make with regard to their investments of capital, e.g. human capital invested in group activities (Grooatert and Narayan, 2004). These two-way causative relationships have the possibility of underestimating the standard errors associated with the parameters in the regression models tested in this study.

A common method is to use the same variable but at an earlier date (McKay and Pal, 2004). Since the 1995 ECV is a cross-sectional survey there is no way of including the past values for the number of bedrooms per person for the same households surveyed in 1995.

To empirically test the direction of the causality I can make use of a set of variables for the physical capital of the household but which are not significantly related to household consumption (Grootaert and Narayan, 2004). Constructing a set of instrumental variables from the same survey is difficult considering that almost all of the variables that could be used for physical capital will suffer the same problem as the number of bedrooms per person. House building material may show correlation with the number of bedrooms per person but is also likely to have a direct impact on consumption via the imputed value for rent.

A simpler option is to remove the variable from the regression models; this has the effect of reducing the overall fit of all the models but does not radically nor consistently change the coefficients of the other variables.

2.4.3 District-level models

Regression models using data at the district level were estimated, using first solely variables representing the environmental context data, and subsequently with additional variables aggregated from the households in the 1995 ECV.

The first model uses the mean values for all variables. The coefficients of the explanatory variables are only slightly significant in the case of the mean number of dry-months and for the mean slope values (Table 15). The signs of the coefficients are, however, as expected with mean consumption rising as the number of dry months and slope decrease. The model was re-calibrated using the median values for the dependent variable. None of the variables were significant in this model and the sign of the coefficient for land suitability was also not as expected. Sub-models were run for the rural and urban locations and the coefficients were generally insignificant with only the mean slope values significant at the 95% level in the urban model.

Table 15. Standardised β, significance levels and rankings of importance of explanatory variables in district level models

		All Areas (mean) n=55		All Areas (median) n=55		Urban (mean) n=32		Rural (mean) n=31	
NC1_DRY	-	-.334 *	2	-.321	1	-.474	2	-.292	2
NC2_LAND	+	.028	5	.000	5	.179	4	.146	3
NC3_SLP	-	-.370 *	1	-.310	2	-.605 *	1	-.323	1
NC4_NVEG	+	.204	3	.181	4	.328	3	**-.050**	4
PC1_ACC	-	-.126	4	-.184	3	-.113	5	**.028**	5

* Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9% level

Figures in **bold** type indicate parameters with a sign different to that expected.

The inclusion of the aggregated household level variables in the models tends to increase the values of the standardised betas of the parameter for mean slope (Table 16). Also, in contrast to the model with district-level variables only, the effect of poor access to markets and services is negative for rural households while positive for urban households.

Table 16. Standardised β, significance levels and rankings of importance of explanatory variables in district level models with aggregated household level variables included

		All Areas (mean) n=55		All Areas (median) n=55		Urban (mean) n=32		Rural (mean) n=31	
NC1_DRY	-	-.248 *	2	-.254 *	2	-.539	2	-.082	3
NC2_LAND	+	.102	3	.083	4	.042	5	.039	4
NC3_SLP	-	-.602 ***	1	-.510 ***	1	-.783 **	1	-.647 **	1
NC4_NVEG	+	.063	4	.033	5	.112	3	**-.039**	4
PC1_ACC	-	**.005**	5	-.097	3	**.044**	4	-.184	2
HC1_EDUL	+	-.100		-.140		.081		-.008	
HC2_LITS	+	.418 ***		.417 **		.489		.443	
HC3_FTRN	+	.319 *		.361 **		.040		.272	
NC1_LOWN	+	-.118		-.075		.066		-.167	
NC1_LRNT	+	.186		.221		-.339		.192	
N2_LCOW	+	.218		.228		-.114		.543	
NC3_LMED		-.146		-.006		.281		-.143	
NC4_LSML	+	-.036		-.144		-.003		.021	
NC5_LDFT	+	.007		-.010		-.024		-.106	
NC6_AGWK		-.344 **		-.313 *		-.239		-.346	

* Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9% level

Figures in **bold** type indicate parameters with a sign different to that expected.

2.4.4 Multilevel models

2.4.4.1 Urban households

In the household level model for urban areas human capital variables were consistently important and significant determinants of household well-being (Table 13). This is not the case in the multilevel models (Table 17) and is especially notable for the variable of literacy. Levels of formal training are still highly significant but have less strength than in the household level model. The signs of the relationships do not change.

The social capital variable coefficient is broadly similar to that in the household level model, and in the natural capital group the coefficients for the value of land owned and the number of cows owned are once again strong and are more significant.

As with the household level model the variables representing physical capital are important. The signs of these variables do not differ between the household and multilevel models. This is also the case with the financial capital group of variables. In the multilevel model for urban areas the most important of these variables is the dummy variable for a lump sum payment. The levels of significance are in general higher in the multilevel model and the signs are the same apart from one variable (F5_RTDM_Z) but this is a very weak variable and even in the household models the sign changes between the models for different regions.

The higher-level variables are compared with the coefficients in the district level model. The comparison shows that the values of the standardised parameters are weaker in the multilevel model but are more significant, especially the proxy variable for forest resources (NC4_NVEG_Z), while the signs are as expected.

The model for urban households contains two interaction variables, of which one - the interaction between the dummy variable for income from rent and the contextual variable of the number of consecutive dry months – is highly significant.

2.4.4.2 Rural households

The sign, strength and significance of the human capital variable coefficients in the multilevel model for rural households (Table 17) are similar to those in the household level model (Table 14). The importance of time spent in the community is less strong in the multilevel model.

The size of the coefficients of the natural capital variables are smaller than in the household level model and the coefficient for the value of land owned is less significant. There are also some variables which have a negative relationship with well-being, in contrast to the household level model, such as the value of land which is rented, however this variable is not a significant determinant in either model.

The physical capital variables are very important in both the household and multilevel models. The variable of capital invested in businesses is stronger and more significant in the multilevel model. One difference between the household level models and the multilevel model is that the coefficient for the provision of electricity is negative in the household models and positive in the multilevel model, the importance of this variable, however, is small in both model types.

Financial assets show very strong associations with household well-being in the multilevel model for rural households. The most important variables are the dummy variable for a lump sum payment and the two variables for transfers. As with the household level model the relationship between the dummy variable for transfers and well-being is negative but when the transfers are large the relationship is positive. This pattern is reversed for credit receipts where the dummy variable is positively associated with well-being.

The strength of the district level variables for rural households is not as strong as for the urban households, nor are the coefficients as large as in the district level variable model (Table 15). The signs are, however, consistent with the district level model and the variable which captures the effect of topography (NC3_SLP_Z) is the strongest of the five variables. There is less similarity in the relative differences in the importance of the coefficients when compared to the district level model which includes aggregated household level variables (Table 16) - notably the accessibility variable (PC1_ACC_Z). It should be pointed out however that this variable is not significant in either model.

The model for rural households contains three interaction variables. The interaction between the average slope per district and the number of bedrooms per person is highly significant, while the interaction between the slope and amount of money received as credit is one of the largest coefficient values.

Table 17. Standardised γ, significance levels and rankings of importance of explanatory variables in multilevel model with cross-level interactions

		Urban		Rural	
H1_EDUL_Z	+	0.013	28	**-0.021**	**22**
H2_LITS_Z	+	0.056*	12	0.087***	6
H3_FTRN_Z	+	0.073***	7	0.085***	7
H4_HLTH_Z	-	-0.004	33	0.009	26
S1_TIME_Z	+	**-0.022***	**21**	**-0.039**	**17**
N1_LOWN_Z	+	**-0.068*****	**10**	0.045*	12
N1_LRNT_Z	+	**-0.042**	**15**	**-0.002**	**34**
N2_LCOW_Z	+	0.069*	9	**-0.010**	**24**
N3_LMED_Z	+	**-0.038**	**18**	0.007	29
N4_LSML_Z	+	**-0.010**	**30**	**-0.026***	**20**
N5_LDFT_Z	+	0.006	31	**-0.028****	**19**
N6_AGWK_Z		-0.011	29	-0.044***	13
P1_NBED_Z	+	0.205***	1	0.205***	2
P2_ELEC_Z	+	0.073	7	0.022	21
P3_CPBS_Z	+	0.083***	6	0.435***	1
P4_CPAG_Z	+	0.047	14	0.015	23
F1_LPDM_Z	+	0.097***	4	0.089***	5
F2_LPSC_Z	+	0.020	24	0.003	33
F3_TRDM_Z		-0.039***	17	-0.073***	8
F4_TRSC_Z	+	0.020	24	0.133***	3
F5_RTDM_Z	+	0.005	32	**-0.008**	**27**
F6_RTSC_Z	+	0.022***	21	0.052	11
F7_PNDM_Z	+	**-0.041***	**16**	0.008	27
F8_PNSC_Z	+	0.026*	20	0.004	32
F9_CRDM_Z		0.060***	11	0.044***	13
F10_CRSC_Z	+	0.017**	27	**-0.043**	**15**
NC1_DRY_Z	-	-0.091*	5	-0.031	18
NC2_LAND_Z	+	0.018	26	0.007	29
NC3_SLP_Z	-	-0.135***	2	-0.071*	10
NC4_NVEG_Z	+	0.098***	3	**-0.010**	**24**
PC1_ACC_Z	-	-0.049	13	-0.007	29
P3_CPBS_Z*NC1_DRY_Z		-0.022	21		
F5_RTDM_Z*NC1_DRY_Z		0.028***	19		

P1_NBED_Z *NC3_SLP_Z	0.043***	15
F4_TRSC_Z *NC3_SLP_Z	0.072	9
F10_CRSC_Z*NC3_SLP_Z	0.102*	4

* Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9% level

Figures in **bold** type indicate parameters with a sign different to that expected. Rankings shaded green are the 5 largest standardised coefficients.

2.5 Discussion of findings

In general the household level models seem fairly well calibrated (Table 7 and Table 8), considering the fact that no community level variables are included. There do appear, however, to be several variables that have an opposite effect to the one expected (Table 13 and Table 14). Nearly all of the variables, except the number of days lost due to illness (H4_HLTH), are thought to have a positive effect on well-being. There are also a number of variables whose relationship with well-being is not easy to predict or which have been added as part of an interaction with other assets (e.g. H6_AGWK – the number of agricultural workers).

The average number of years of education of the household (H1_EDUL) has a negative relationship with well-being in three of the eight household level models (Table 13 and Table 14) but the strength of the relationship is not significant. It could be argued, however, that an alternative definition of this variable – for instance concentrating on the maximum years of household education or restricting the measure to the household head might give different results.

The only social capital variable included in the models (time in the community – greater than 10 years or less then 10 years [S1_TIME]) was negative in all seven of the eight household level models and was significant in three of these. A possible explanation for this is that the bonding capital that time in the community represents may be high even in poor households and is a coping mechanism, but this bonding capital is not sufficient in itself to lift a household out of poverty. An alternative interpretation is that this is a poor proxy for social capital.

The differences between the models in the coefficients for owning land are logical. The relationship between owning land (N1_LOWN) and well-being is not significant in the global, Andes or Coastal model, but is positively significant in the Amazon and all rural areas (Table 14), and negatively significant for urban households (Table 13). This suggests that many of the poorer urban households have potentially diverse livelihoods involving agricultural production. Renting land (N1_LRNT) is only significant in the urban model (Table 13) where, as with land owned, the relationship with well-being is negative.

Livestock, whether small (N4_LSML) or large (N2_LCOW & N5_LDFT), are almost universally associated with lower levels of well-being. This is even the case in the rural model where small and draft animals are significant variables (Table 14). This is perhaps understandable in the case of small animals which might be owned by households that cannot afford cattle, but is less obvious for draft animals. A possible explanation for the latter variable might be that richer households are able to buy and maintain motor-vehicles or farm machinery which would replace the draft power of animals. Cattle are significantly associated with higher well-being in the Andean model but this relationship is less strong in the other regions and the direction of the relationship also varies.

Households with large numbers of agricultural workers (N6_AGWK) are associated with low levels of consumption. This perhaps highlights the poor rates of return on labour invested in agriculture as opposed to other employment sectors. This is to be expected in urban settings (Table 13) but the relationship is actually stronger in the rural model (Table 14), perhaps underlying the importance of non-farm income in rural areas.

Physical capital, especially when invested in a business (P3_CPBS) or the household (P1_NBED), is strongly associated with higher well-being. Investment in agricultural infrastructure and equipment (P4_CPAG), however, is not significant.

When interpreting the financial capital variables an interesting discussion is the difference in the five types of financial transfers: (i) a lump sum payment (F1_LPDM

& F2_LPSC); (ii) a transfer from friends, family or other source (F3_TRDM & F4_TRSC); (iii) rent charged on a property (F5_RTDM & F6_RTSC); (iv) a pension (F7_PNDM & F8_PNSC); and, (v) credit (F9_CRDM & F10_CRSC). Both credit and lump sum payments are highly significant in the majority of the models regardless of the size of the transfer. Transfers from family and pensions are generally associated with lower well-being; however, if these are large quantities there is a positive association with consumption. Similarly rent can be either positively or negatively associated with well-being depending on the model, but the size of the rent payment is positively significant in three of the models, but is less significant when urban and rural households are tested in separate regional models (Table 13 and Table 14).

What these results show is that a greater quantity of a household asset is not always associated with higher levels of consumption *vis-à-vis* households with lower quantities of the same asset. The results also show that the models of well-being are different according to the biophysical and cultural regions of Ecuador, and between the urban and the rural sectors. This implies that an assessment of vulnerability which is based on household assets should take into account different assets according to the location of the household.

Models at the district level using the mean value for consumption are in general poorly calibrated (Table 9) although the relationship between the explanatory variables is by and large as expected (Table 15). The model of rural households, where one would expect a larger contribution of biophysical variables, explains very little of the variation of mean consumption.

Despite the small sample size[32] it was possible to include aggregated values of selected household level variables without altering the general significance of the model, leading to greater explanation of the variance of aggregated household consumption at the district level. The effect was less marked for urban households but underlines the benefit of taking into account variables at different levels (Table 16).

[32] Compared to Farrow et al., 2005, for example

The interaction between district and household level variables is unclear, although the effect of the proportion of household labour invested in agriculture (NC6_AGWK) is likely to be influenced by the agro-ecological potential of the district (NC1_DRY, NC2_LAND and NC3_SLP). It is possible that district level variables will have effects on well-being independently of the household level variables so I conclude that the two levels of variables ought to be combined using a multi-level modelling framework.

In a multilevel framework significant improvements in model fit can be observed when district level variables are included (Table 12). There are also improvements in the model calibrated using rural households when the slope of some of the household level variables is allowed to vary according to the district. An exploratory analysis also shows that introducing interaction terms between household and district level variables improves the fit of the model even though the interactions are not those thought to have an effect on household well-being. The size of the intra-district correlations suggest that the districts have a heterogeneous composition of households and that most of the variance is between households rather than between districts. This was also the case when the intra-class correlations were calculated for the sampling domains of the 1995 ECV or the conventional Coastal, Andean and Amazon regions of Ecuador.

In the multilevel model for urban households it can be seen that three of the strongest correlates of household consumption are district level variables (Table 17). Two of these – water (NC1_DRY_Z) and forest resources (NC4_NVEG_Z) – could be considered as assets in their own right while average slope per district (NC3_SLP_Z) is either a proxy for other factors that have not been considered such as the socio-cultural characteristics which are not captured by the traditional regions of Ecuador (which is also suggested by Farrow et al., 2005), or else an interaction as hypothesised. Interactions between the slope variable and household level variables do not improve the model fit however (Table 12). The significant interaction effect between receiving a rent payment and the number of dry months (F5_RTDM_Z*NC1_DRY_Z) seems to have little explanation especially as the interaction term with the amount of rent received (F5_RTSC_Z) was not significant.

For the rural households it was noticeable that the variable for the proportion of agricultural workers (N6_AGWK_Z) had no impact on the model as an interaction term and showed no significant variance in the slope when this component of variance was analysed. As with the household level models the most important correlates of consumption were human, physical and financial capital variables (Table 17).

In conclusion the analysis in this chapter has shown that the consumption levels are poorly explained by the assets for which data are available. Regional and sectoral differences in models are suggested by the household and district level models and have been confirmed by the important correlations between district level variables and household consumption in the multilevel models. The multilevel modelling framework allows for the treatment of spatial non-stationarity in the model of household well-being although a thorough analysis of spatial dependency and spill-over effects is not possible given the small sample of districts; a more thorough study of spatial dependency is tackled by Farrow et al. (2005). There is, nevertheless, greater variance of consumption at the household level than between districts, sectors or regions, and this variance is not being captured in the explanatory variables chosen for this analysis. It has been shown that definitively testing the direction of causality is difficult, given the available data. Removing suspect variables has been shown to have little effect on the coefficients of the other variables.

The variables that are seen to be important correlates of consumption in the multilevel regression models for urban and rural households will be analysed in the context of their susceptibility to the hazards associated with the El Niño phenomenon in Chapter 5. The next chapter, however, will analyse the evidence for the impact of the 1997-98 El Niño event on household well-being.

Chapter 3 : Impacts of the 1997-98 El Niño event on household well-being in Ecuador

3.1 Introduction

Susceptibility of assets, exposure to floods and landslides, and pre-event well-being levels are the key determinants of the vulnerability of households to low levels of well-being. Chapter 2 has highlighted the links between assets and well-being (consumption) at the household level. In Chapter 3 I use some of the models from Chapter 2 to examine the impact of the 1997-98 El Niño phenomenon upon well-being outcomes. The aim of this chapter is to examine whether in the districts affected negatively by floods and landslides the levels of household well-being reduced in comparison with the rest of the country.

Anecdotal evidence exists for the long and medium-term impacts of the 1997-98 El Niño event and assessments have been carried out at the national, sectoral or provincial level. A study of the health sector showed, for instance, that the cost of rehabilitating health facilities would amount to US$3 million (Ministerio de Salud Pública, 1999). However, to date there have been no studies on the impact of the event on the welfare of all Ecuador's households. Vos et al. (1999), following a study by the Economic Commission for Latin America and the Caribbean (Comisión Económica para América Latina y el Caribe, 1998), attempted to quantify the economic and social cost of the impact in the rural sector, but the authors recognised that the effects were still being felt when the study was conducted, therefore no data were available to test their estimations.

National statistics reported by the World Bank (2007) show that per capita GDP dropped sharply in the year after the 1997-98 El Niño event (Figure 7) suggesting a potential association between El Niño and household well-being.

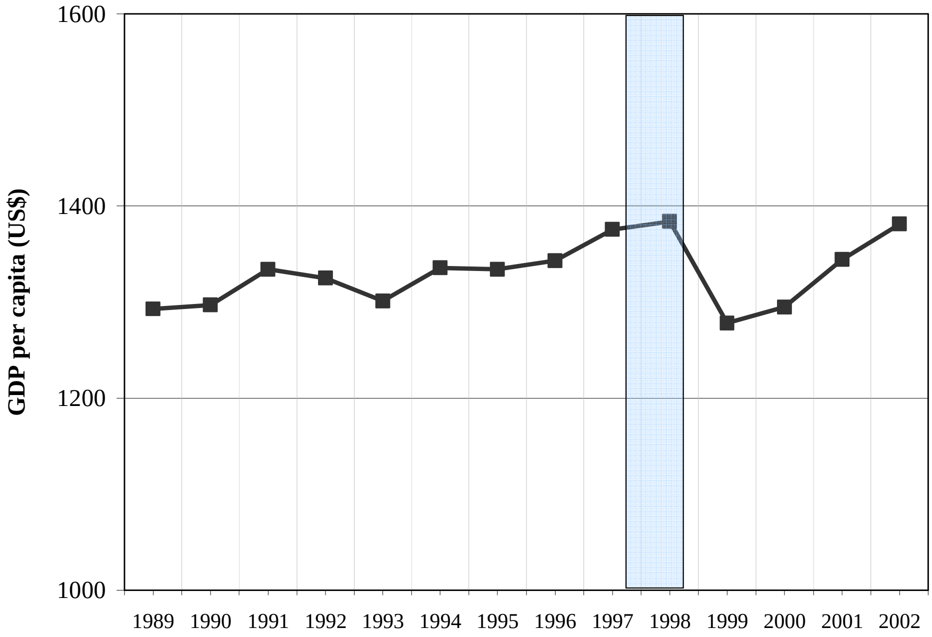

Figure 7. GDP per capita in Ecuador 1989-2002 with 1997-98 El Niño event highlighted in blue

However, there were other pressures on the national economy at the same time (Vos et al., 1999) that could have led to a reduction in national GDP. The most notable was that Ecuadorian revenues from oil were affected by the global decline in prices between 1997 and 1999 (Figure 8). Changes in oil prices are significant since oil revenues are an important component of total exports in Ecuador, amounting to 10% of GDP in the mid-1990's (Fischer, 2000). Other factors that contributed to the Ecuadorian economic recession were the global financial crisis and the loss of confidence in the Ecuadorian financial sector resulting in the collapse of institutions and the default on interest payments on international loans (Brady bonds) in September 1999 (de la Torre, et al., 2001; Comisión Económica para América Latina y el Caribe, 1999).

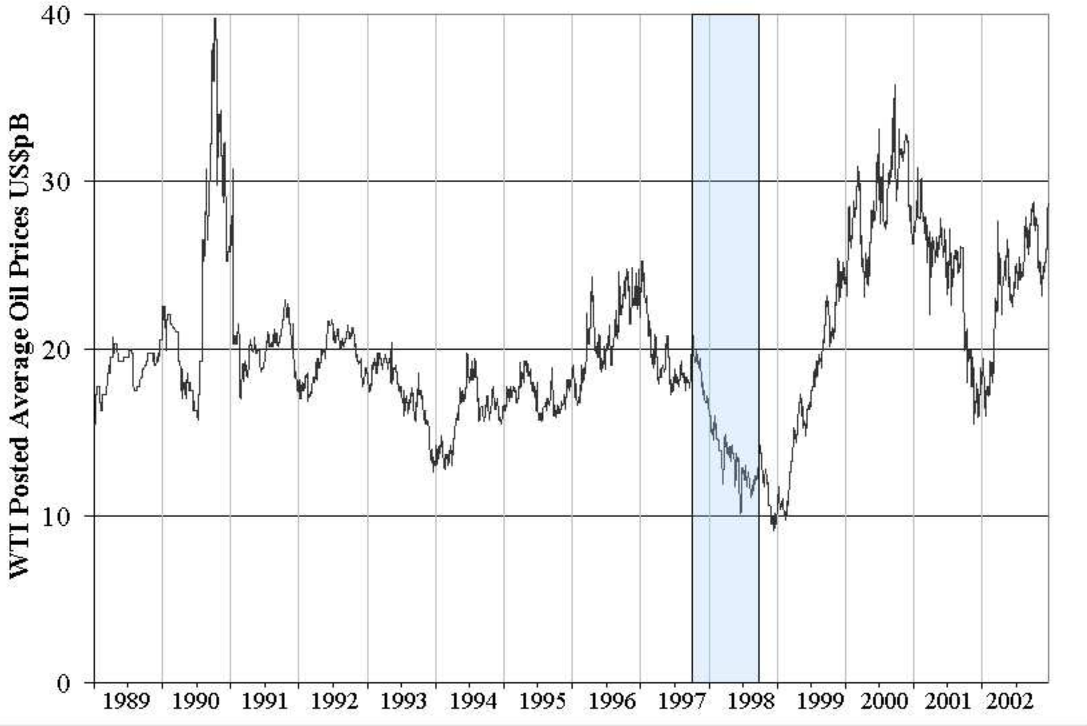

Figure 8. Oil prices (US$/Barrel) 1989-2002[33] with 1997-98 El Niño event highlighted in blue

The study by Vos et al., concludes that the impacts of the 1997-98 El Niño event upon welfare would be felt in two ways: firstly in the reduction in income of small farmers due to crop losses as a result of flooding; and secondly, increased levels of infectious diseases due to destruction or inadequacies of the sanitary system and poor access to safe water affecting both urban and rural populations. Further costs would also need to be absorbed by local or national governments, such as the rehabilitation of infrastructure destroyed during the event, such as roads, schools and hospitals. Given that these potential costs would be disproportionately borne by households in the areas affected by the El Nino phenomenon it is hypothesised that negative changes in welfare would be similarly greater in the affected areas.

This chapter starts by discussing the various sources of information that can be used to estimate the spatial distribution of well-being before and after the El Niño event of

[33] http://upload.wikimedia.org/wikipedia/en/thumb/2/2f/Oil_Prices_Medium_Term.png/800px-Oil_Prices_Medium_Term.png

1997-98. It will then focus upon the various sources of information that can be used to identify the geographical locations where the impacts of El Niño were most severe. Associations between changes in well-being and the 1997-98 El Niño event will then be analysed and discussed.

3.2 Data

3.2.1 Changes in household well-being

In the previous chapter I discussed the most appropriate indicator of household well-being and concluded that I would use consumption expenditure. This is a good indicator for models which use household level data from a cross-sectional survey – such as the ECV (Instituto Nacional de Estadística y Censos, 1995; Instituto Nacional de Estadística y Censos and World Bank, 1998).

Two issues need to be addressed when comparing well-being outcomes over time, the first is the unit of analysis and the second is the value of the well-being variable.

Dealing with the first issue, I must ensure that I compare the same units of analysis, this implies that if the consumption of individual households is analysed (as in Chapter 2) at time t_1, then those same households need to be observed at t_2. This is only achieved when longitudinal or panel data are available. Panel data are two-dimensional datasets with the same households or individuals observed at different time periods for multiple variables. Examples of panel data sets that capture consumption or income include the British Household Panel Survey (Taylor et al., 2007), the US Panel Study of Income Dynamics (Hill, 1992), and the DNBHS[34] from the Netherlands. Panel data sets are rarer in less developed countries (Baulch and Hoddinot, 2000), and where examples exist they are often of limited geographical scope (e.g. Huigen and Jens, 2006; Bhargava and Ravallion, 1993). In Ecuador the households surveyed in the 1995 and 1998 ECV (data sources presented in the previous chapter) are different (INEC 1995b; INEC and World Bank, 1998) so a longitudinal study of individual households over a wide geographical area is not possible. Instead I will compare groups of households aggregated at the district level.

[34] For a description of the dataset refer to Nyhus and Pons, 2004

The second challenge is to ensure that the values being compared are the same. If a particular food item is being analysed over time then this is not a problem (e.g. Maki, 2006). Where consumption has been monetized, however, such as in the 1995 survey of living standards in Ecuador there will be difficulties in comparing the absolute values of consumption. This is because changes in the prices of goods and services will alter the monetary values necessary to satisfy the needs of the household.

An alternative to consumption and one measure often used in less developed countries is poverty. Poverty at the household level implies the non-satisfaction of a basic need or a low level of some well-being outcome such as income or consumption. The well-being threshold is often decided for a particular context (such as a specific country) and is commonly referred to as the poverty line (Lanjouw, 1998). The incidence of poverty for groups of households is the proportion of households below the poverty line. Thus the rate or severity of poverty for groups of households is directly related to levels of consumption at the household level. Given these inter-relations both consumption expenditure and poverty will be considered below as indicators of well-being and the results compared.

Consumption expenditure and poverty data can be calculated for the whole of Ecuador using the 1995 ECV as well as for the representative domains. These domains, however, are not at a spatial resolution that allows a test of the hypothesis that changes in well-being are associated with the impacts of the 1997-98 El Niño phenomenon (section 2.3.2). The most suitable instrument for providing district-level summaries of consumption and the calculation of poverty indicators is the population and housing census. This census is carried out roughly every 10 years and despite the fact that consumption expenditure is not captured in the census there have been efforts to estimate consumption based on the relationships between consumption and some key household characteristics derived from the ECV household surveys. The procedure is based on the construction of multivariate regression models using the ECV, taking as the dependent variable consumption expenditure per person, and selecting as explanatory variables those which are found in both the ECV and the census – typically including housing conditions, education, employment and ethnicity. This procedure, called small area estimation (Ghosh and Rao, 1994) has been utilised in Ecuador taking both total consumption and poverty as the dependent variables (Larrea et al., 1996: Elbers et al., 2003; Larrea, 2005), and has also been used by the World Bank in numerous countries in the world to project household surveys onto population and housing censuses (e.g. Alderman et al., 2002; Elbers et al., 2002).

The data for total consumption and poverty used in this study are estimates derived by Larrea et al. (1996), and Larrea (2005) from models calibrated using households in the 1995 and 1998 ECVs, and applied to the 1990 and 2001 censuses respectively. The number of districts in 2001 exceeded that in 1990 but in some cases it has been possible to construct consumption aggregates for these new districts using census sectors (Larrea et al., 1996; Larrea, 2005; Larrea, personal communication). Appendix 4 describes the problems of changing boundaries in more detail.

3.2.1.1 Z-scores of mean household consumption between 1990 and 2001

The 1990 and 2001 household consumption estimates were aggregated at the district level and the z-scores calculated from these. The creation of Z-scores relative to the mean value of household consumption for all districts allows the comparison of absolute consumption per district between 1990 (Figure 9) and 2001 (Figure 10).

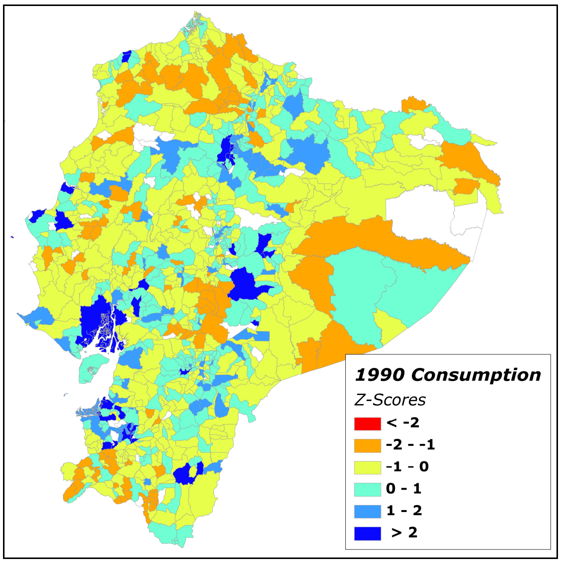

Figure 9. Z-scores of average household total consumption per district in 1990

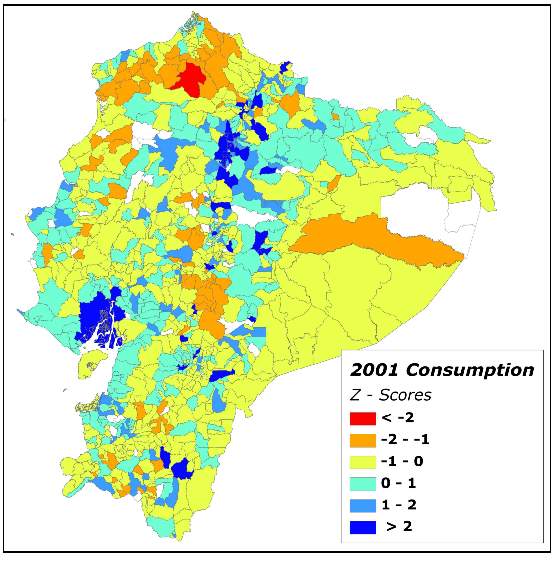

Figure 10. Z-scores of average household total consumption per district in 2001

The values of the z-scores are dependent on the arithmetic mean value and the standard deviation. The histograms of these variables for both datasets (Figure 11 and Figure 12) shows that there was perhaps greater dispersion of values in 1990 than in 2001[35] although in 2001 there were slightly more districts with mean household consumption greater than 3 standard deviations from the arithmetic mean[36].

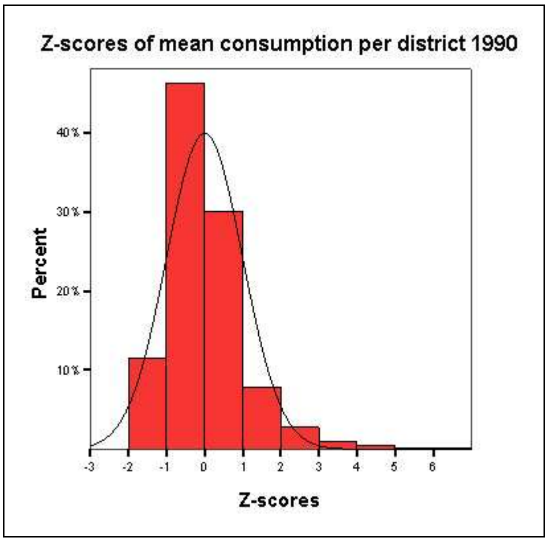

Figure 11. Histogram of z-scores of average household total consumption per district in 1990

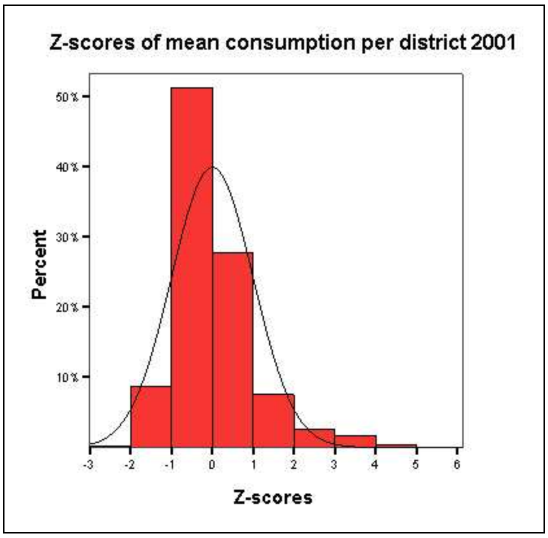

Figure 12. Histogram of z-scores of average household total consumption per district in 2001

In order to examine changes in consumption between these two time periods the Z-scores in 1990 were subtracted from the Z-scores in 2001. The results are presented in Figure 13, negative values indicate a reduction in average consumption relative to the rest of the nation. There does not appear to be a strong spatial pattern associated with the changes in the z-scores, although potential clusters exist in the southern Coastal and Andean regions as well as Esmeraldas province in the northern Coastal region.

[35] The change in kurtosis values is small, 4.778 in 1990 and 4.396 in 2001
[36] There were 16 districts with z-score values greater than 3 in 1990 and 21 districts in 2001.

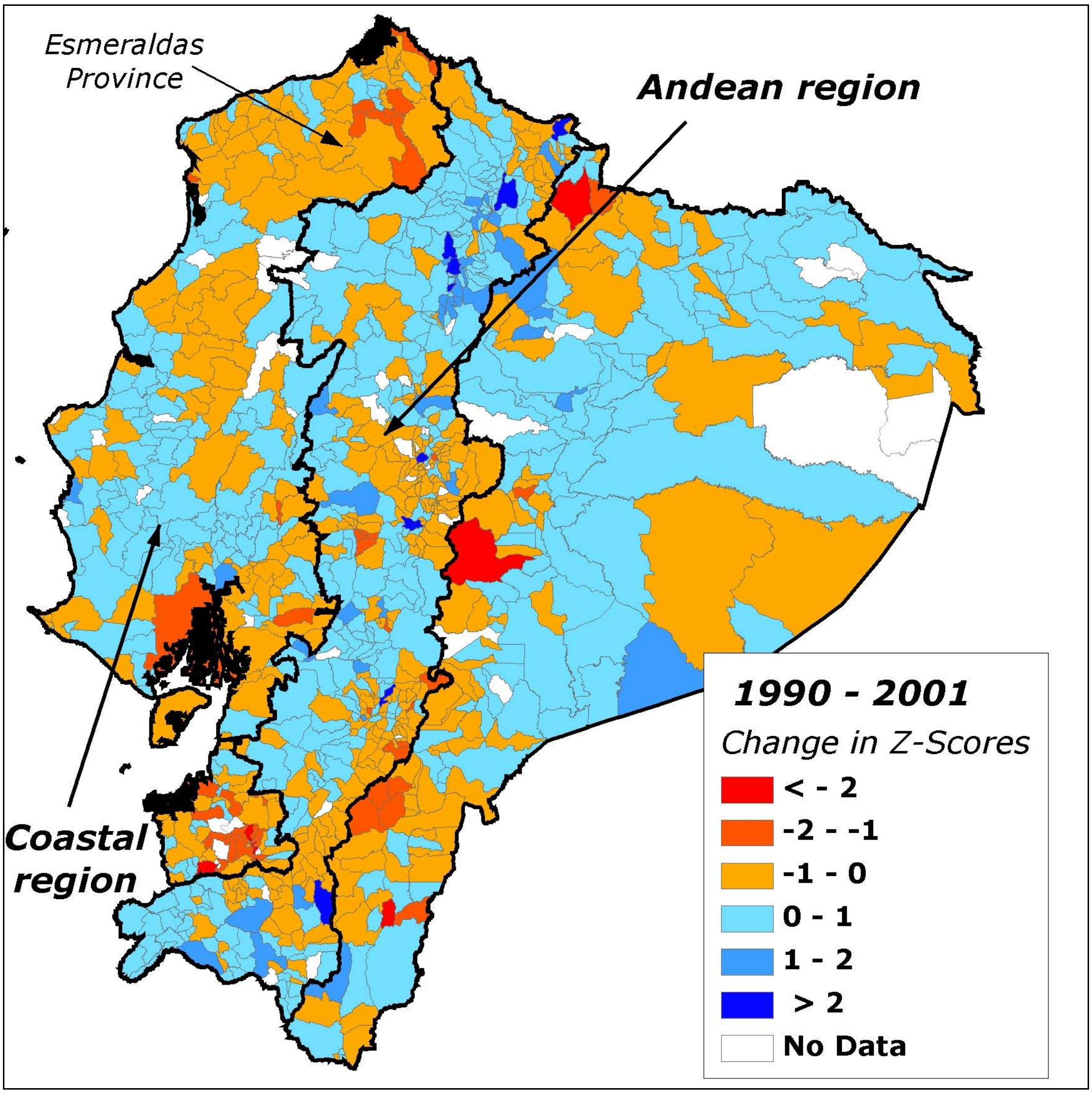

Figure 13. Change in Z-scores of average household total consumption per district between 1990 and 2001. Districts in white have missing consumption data for either or both 1990 and 2001.

An alternative way of presenting this data is to simplify the districts depending upon whether the Z-score has improved and deteriorated and to then group these districts by the region within which they are located (Table 18). This table shows that the proportion of districts in the Coastal region that deteriorated was larger than for the other two regions, and suggests that a more thorough analysis of the changes and the link to the 1997-98 El Niño phenomenon is justified.

Table 18 Sum of districts for each region according to change in z-score of average household consumption

Change in consumption z scores 1990-2001	Region			Total
	Coastal	Andean	Amazon	
Worse	151	224	76	451
Better	123	265	98	486
Total	274	489	174	937

3.2.1.2 Poverty lines

An alternative response variable to consumption is the use of poverty lines to enable comparison over time. The poverty line is an absolute value which has real meaning at a particular point in time and is a monetary amount that has been calculated to provide the household a basket of basic goods and services (Lanjouw, 1998). If the household consumes less than this amount it is deemed poor. The proportion of households in a district below this poverty line is the headcount ratio and is the most common indicator of poverty. Others in the same family of indicators are the poverty gap and poverty severity (Foster et al., 1984). The poverty data were calculated in the same way as consumption although slightly different regression models were employed (Larrea et al., 1996; Larrea, 2005).

As with consumption the use of z-scores of poverty allows an alternative comparison over time. The distribution of the z-scores, and indeed the change in z-scores over time, is very similar to the poverty headcount ratio (Figure 14), suggesting that the use of the poverty z-scores in the analysis is probably unnecessary. The results of the associations between the poverty z-scores and impact variables will only be reported if there are significant changes between this indicator and the change in the headcount ratio.

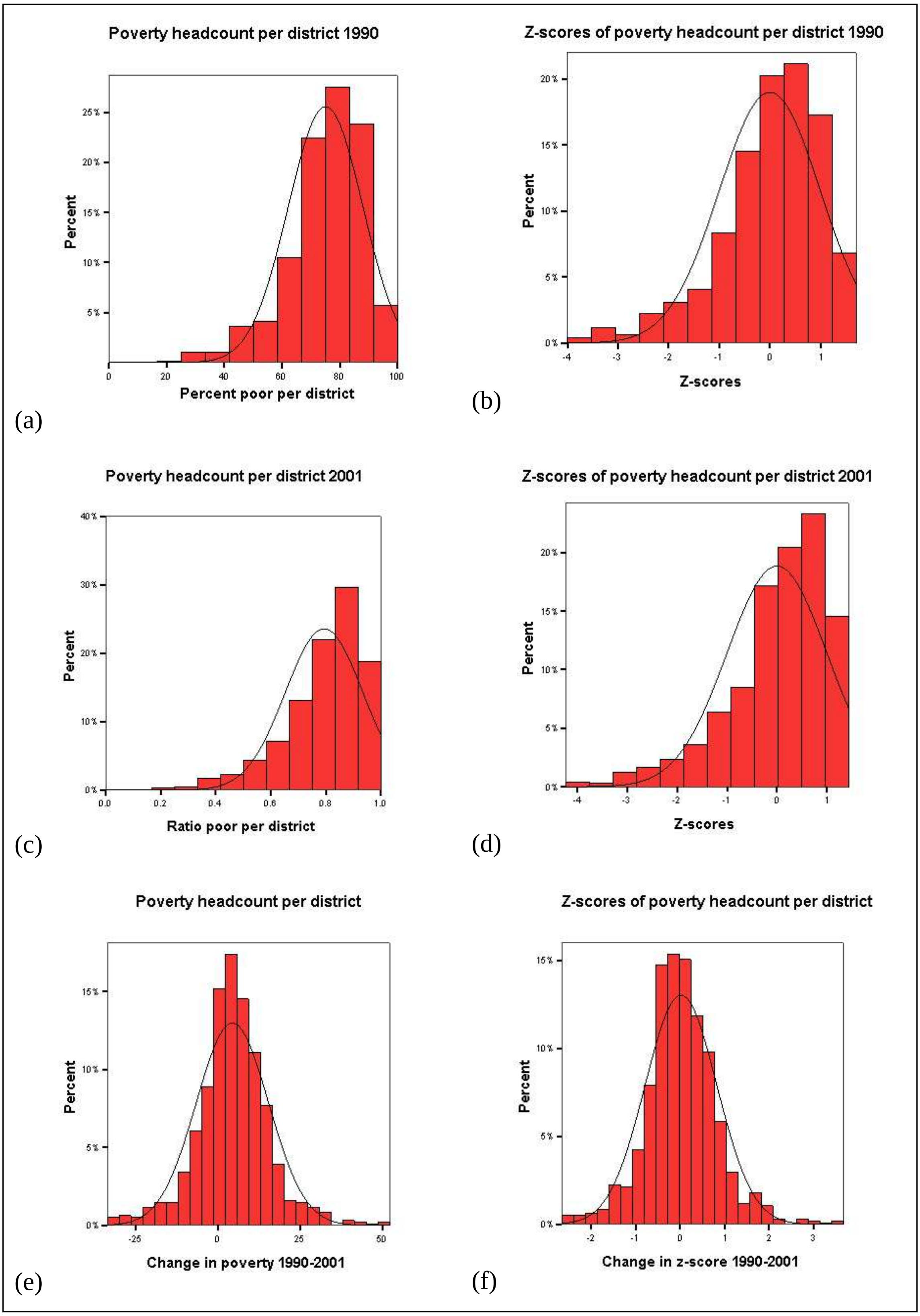

Figure 14. Histograms of poverty indicators: (a) Headcount ratio 1990; (b) Z-score 1990; (c) Headcount ratio 2001; (d) Z-score 2001; (e) Change in headcount ratio 1990-2001; (f) Change in z-score 1990-2001

Figure 15 shows the percentage of poor households per district in 1990, while Figure 16 shows the same variable in 2001. These are followed by the change in the percentage of households below the poverty line (Figure 17). More districts experience deterioration in the poverty levels than in the z-scores of the mean levels of consumption. It is quite possible for districts to experience a reduction in the z-scores of the mean values of household consumption but contain fewer households below the poverty line. Similarly it is possible for all the districts to experience higher poverty levels but maintain the same z-score.

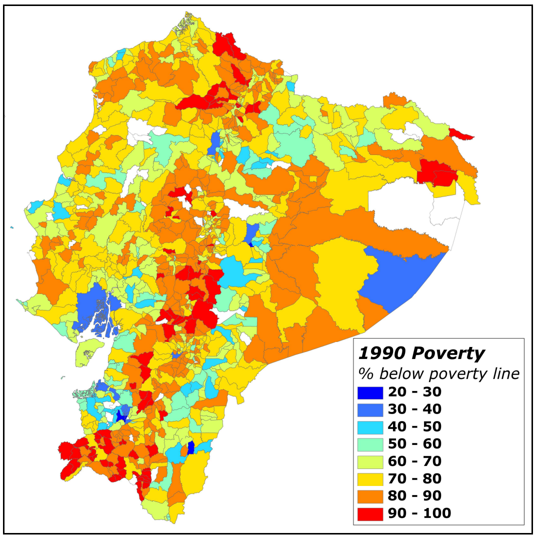

Figure 15. Poverty headcount ratio of household total consumption per district in 1990

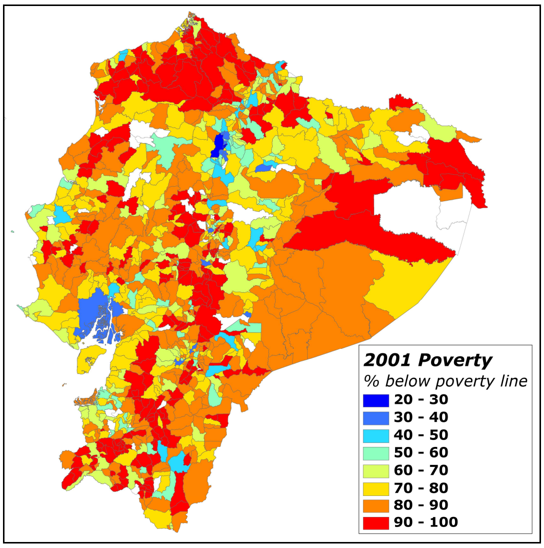

Figure 16. Poverty headcount ratio of household total consumption per district in 2001

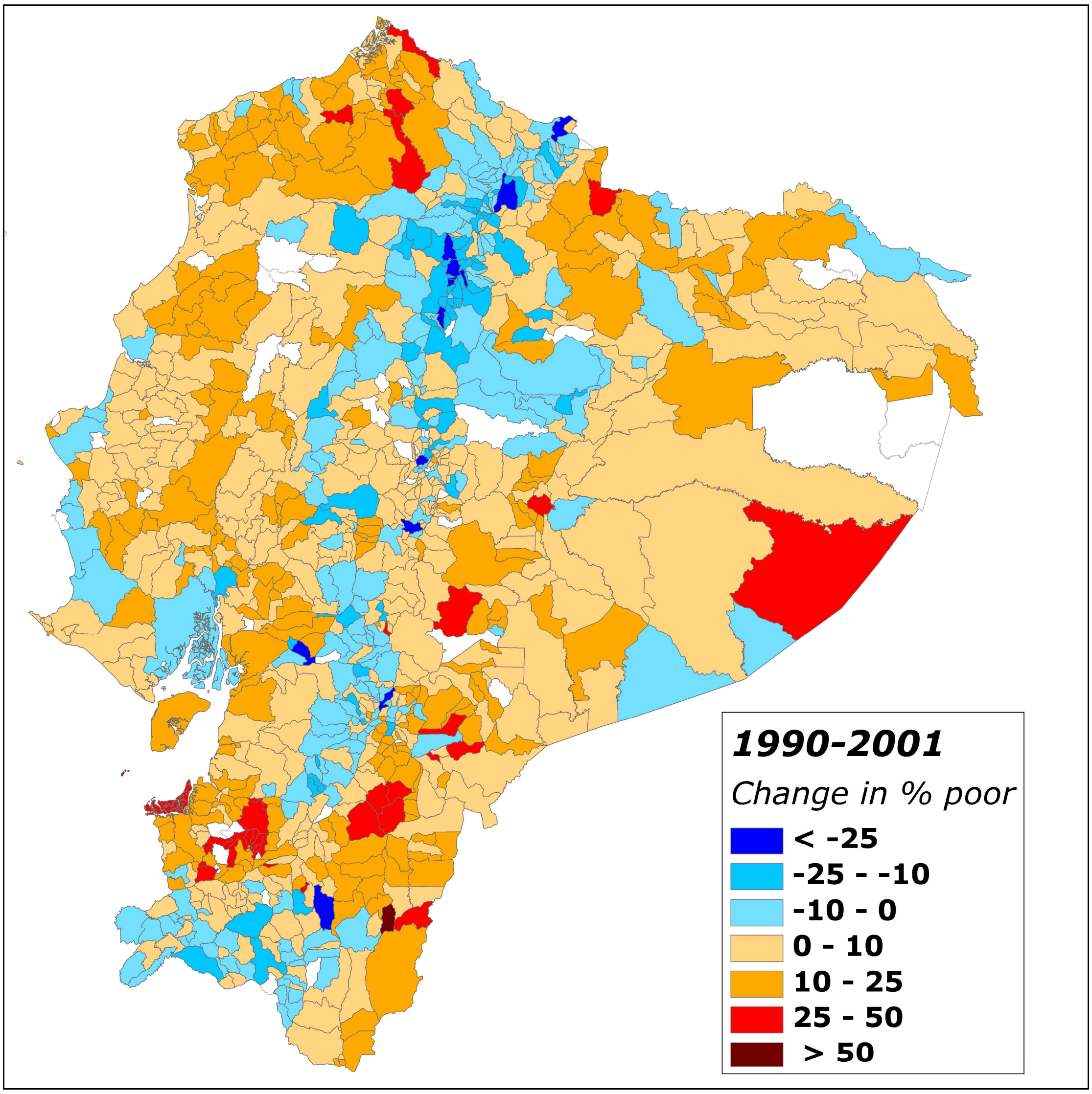

Figure 17. Change in poverty headcount ratio of average household total consumption per district between 1990 and 2001

The distribution of these changes, however, is even more skewed than in the case of mean consumption with the Coastal and Amazon regions particularly affected (Table 19).

Table 19. Sum of districts for each region according to change in poverty headcount ratio 1990-2001

Change in poverty headcount ratio 1990-2001	Region			Total
	Coastal	Andean	Amazon	
Worse	257	256	151	664
Better	17	233	23	273
Total	274	489	174	937

3.2.1.3 Differences between well-being indicators

Changes in the mean consumption in a particular district may have no effect on the poverty headcount ratio; this is because increases in consumption of households above the poverty line have no effect on poverty. Indeed if only the already rich households get richer then it is possible that the number of households below the poverty line could actually grow despite increases in the mean consumption (Lanjouw, 1998; Chaudhuri et al., 2002). As such one would not expect a perfect correlation between improvements in districts' poverty levels and mean household consumption. Figure 18 shows the comparison of changes in consumption and poverty between 1990 and 2001.What is striking about this figure is the regional pattern of differences between poverty and consumption. Many districts in the Amazon and Coastal regions show increases in poverty yet experience an increase in mean consumption levels, while in the Andes region many districts see an opposite result. These imply that the benefits of economic growth experienced during the 1990's were not equally shared in many districts, and in terms of this study highlight the need to take poverty as well as consumption into account when investigating the outcome of the 1997-98 El Niño phenomenon.

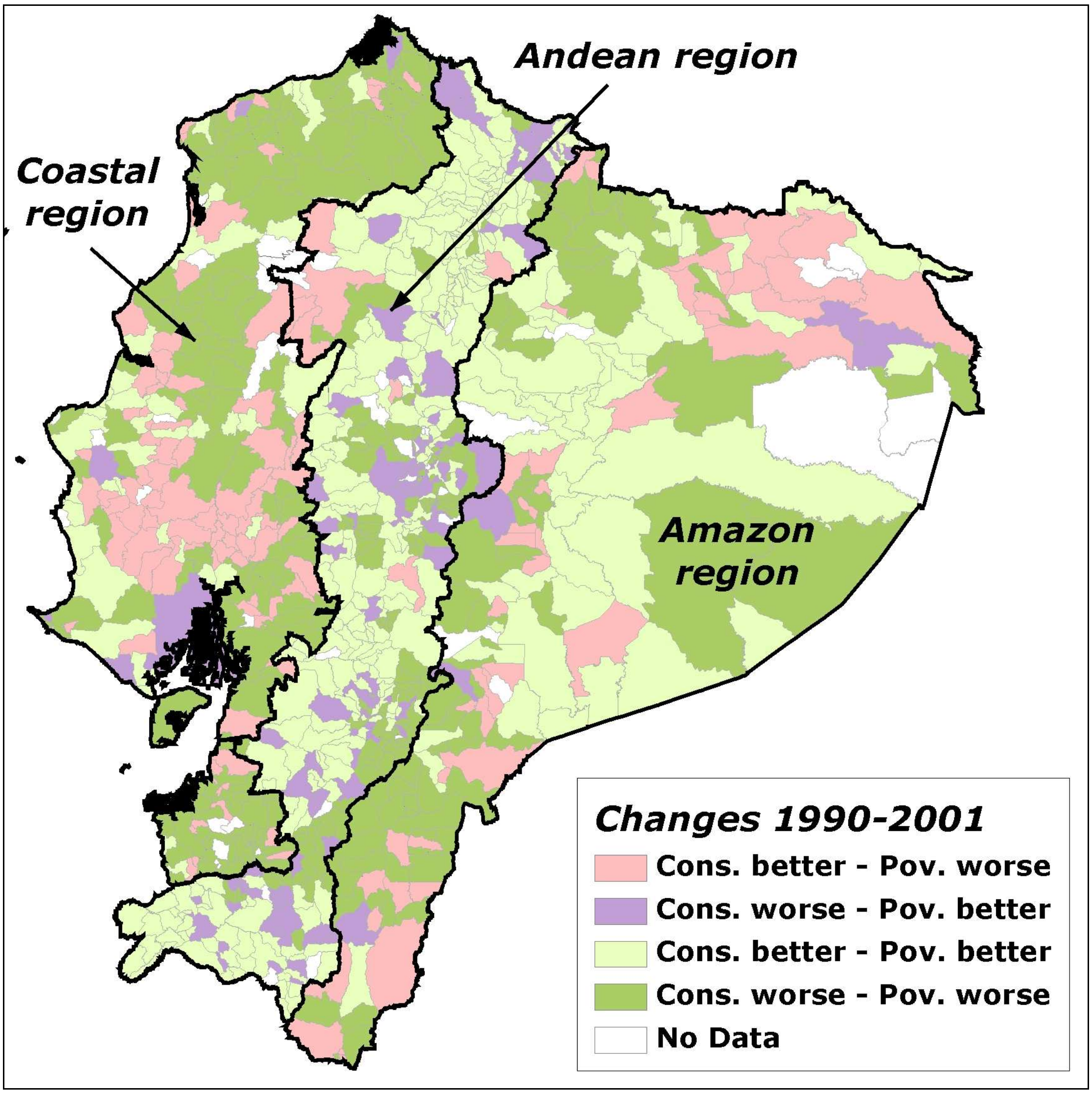

Figure 18. Differences in the changes in Z-score of average household total consumption per district and Z-score of the district poverty headcount ratio between 1990-2001

3.2.2 Impacts of El Niño

The ideal data source of the impacts of the1997-98 El Niño event would include information on the location of an incident, the type of impact, and the magnitude of damages. Three major types of information are available regarding the impacts of the El Niño event of 1997-1998, listed in order of likelihood of satisfying the criteria above:

1 – Geo-referenced databases or inventories of incidents

2 – Maps of exposure, especially large scale floods

3 – Assessments of vulnerability or potential exposure to flooding and landslides

I will now consider the potential sources of each of these to describe the 1997-98 El Niño event.

3.2.2.1 Geo-referenced databases or inventories of incidents

Data on actual impacts have been collated by the *Defensa Civil* (Dirección Nacional de Defensa Civil, 2002) in textual format, the sources are not reported but it is assumed that these incidents were brought to the attention and acted on by the civil defence organisation. The data do not appear in map form but have been collated by according to county (Figure 19). More precise information on the location of each incident is often provided (see Table 20 for example) but without local knowledge or a good gazetteer it is difficult to locate the incidents.

Table 20. Extract from *Defensa Civil* inventory of impacts of the 1997-98 El Niño phenomenon

Date	**County**	**Description**	**Impact**
02/12/1997	Esmeraldas	Tabiazo district flooded	2 families homeless
03/12/1997	Esmeraldas	Rivers Teaone and Esmeraldas burst banks causing flooding in sectors Propicia 1 and 2 of the city of Esmeraldas	30 families affected
04/12/1997	Esmeraldas	Esmeraldas river flooded in the sector of the islands Piedad, Roberto Luis Cervantes and Vargas Torres; Sector Propicia II also flooded	30 families homeless, 13 evacuated to shelters. 320 families temporarily affected
05/12/1997	Esmeraldas	Flooding in districts of Chinca and 5 de Agosto	9 families homeless

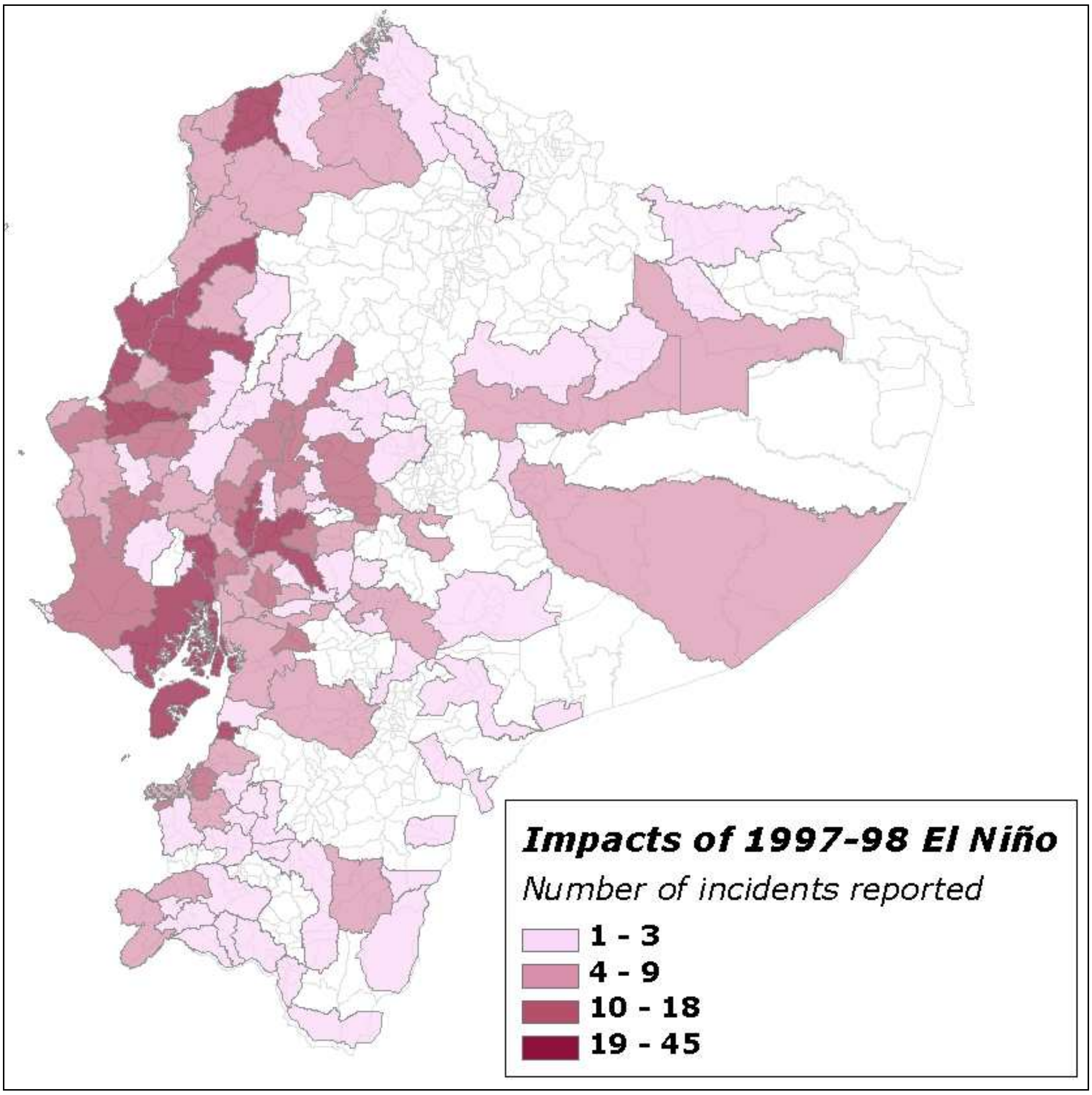

Figure 19. Number of incidents per county reported by the *Defensa Civil*

An alternative inventory of the impacts of the 1997-98 El Niño has been compiled as part of the DesInventar project (DesInventar, 2004). Reports of events have been assembled from local and national media (particularly newspapers), as well as from the *Defensa Civil* and are classed according to the type of event and the damages associated with it. Thus for the period October 1997 to June 1998 there are 333 records whose cause is stated as “El Niño” and 39 due to rainfall, in addition there were 43 incidents whose cause was unknown or not listed. These data have been aggregated by DesInventar to a county level (Figure 20), allowing for comparison with the *Defensa Civil* source.

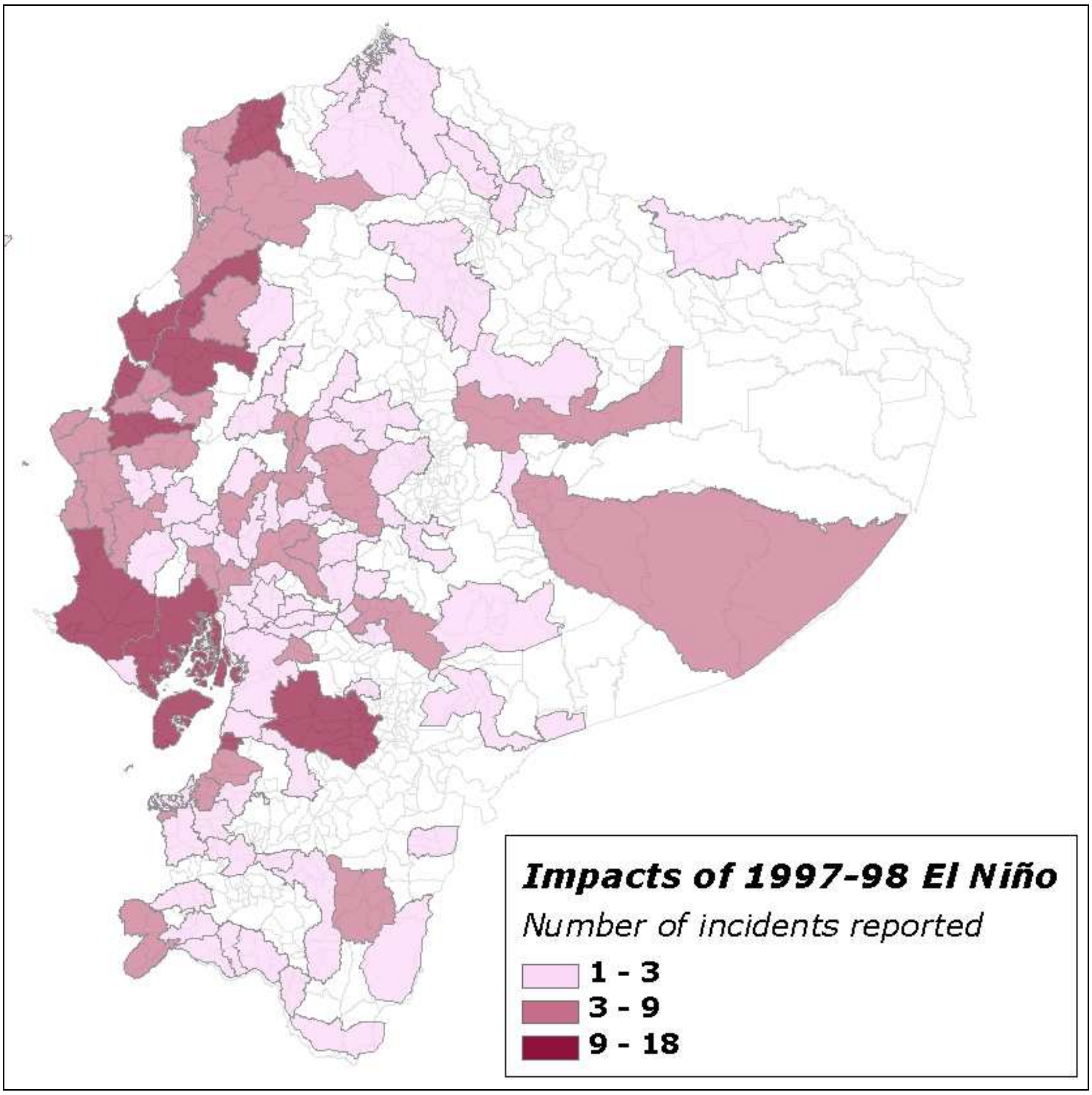

Figure 20. Number of incidents per county reported in DesInventar

There are some inconsistencies between incidents reported by DesInventar and the Defensa Civil. The DesInventar source tends to under-report the causes of incidents attributed to the El Niño phenomenon and while the patterns are similar (Figure 21) the DesInventar source attributes incidents in a number of counties in the Andean region to the El Niño phenomenon which are not reported by the *Defensa Civil*.

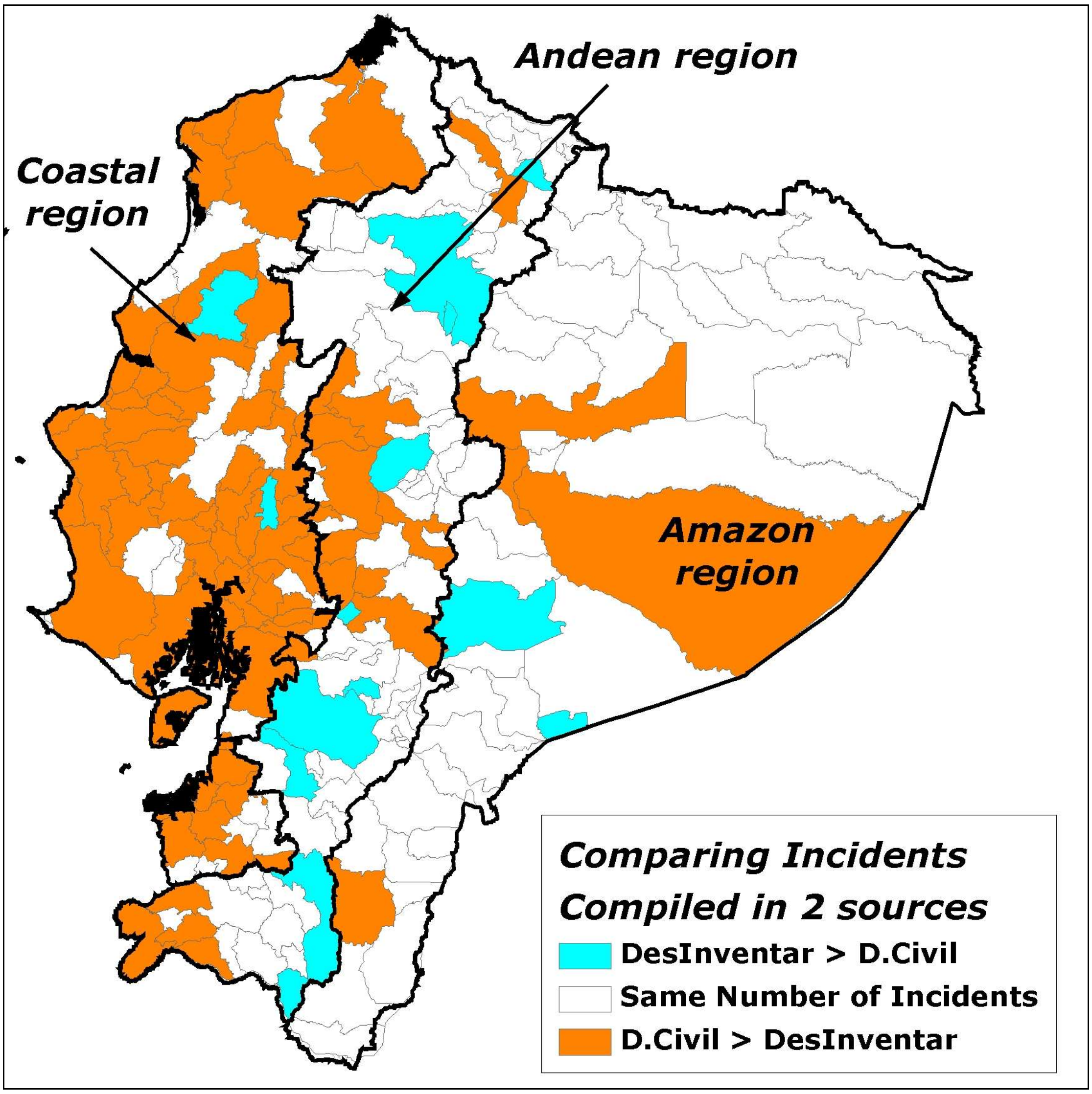

Figure 21. Number of incidents per county reported in DesInventar compared with the number of incidents reported by the *Defensa Civil*

Both sources are liable to reporting bias (smaller events are unlikely to be reported in the national media and many remote areas are not well served by the *Defensa Civil*), but DesInventar has the advantage of providing more information on damages in a format that is easy to use and draws on more sources than the *Defensa Civil* report.

For each incident the severity is noted according to the number of deaths, injuries, the number of people affected (Figure 22) or evacuated, homes destroyed or affected, hectares of crops destroyed, hospitals or schools affected and, where known, the monetary cost of the incident.

The advantage of this source over the report from the *Defensa Civil* is that the data are provided in tabular format. This dataset thus meets the criteria stated above of a suitable source of information on impacts.

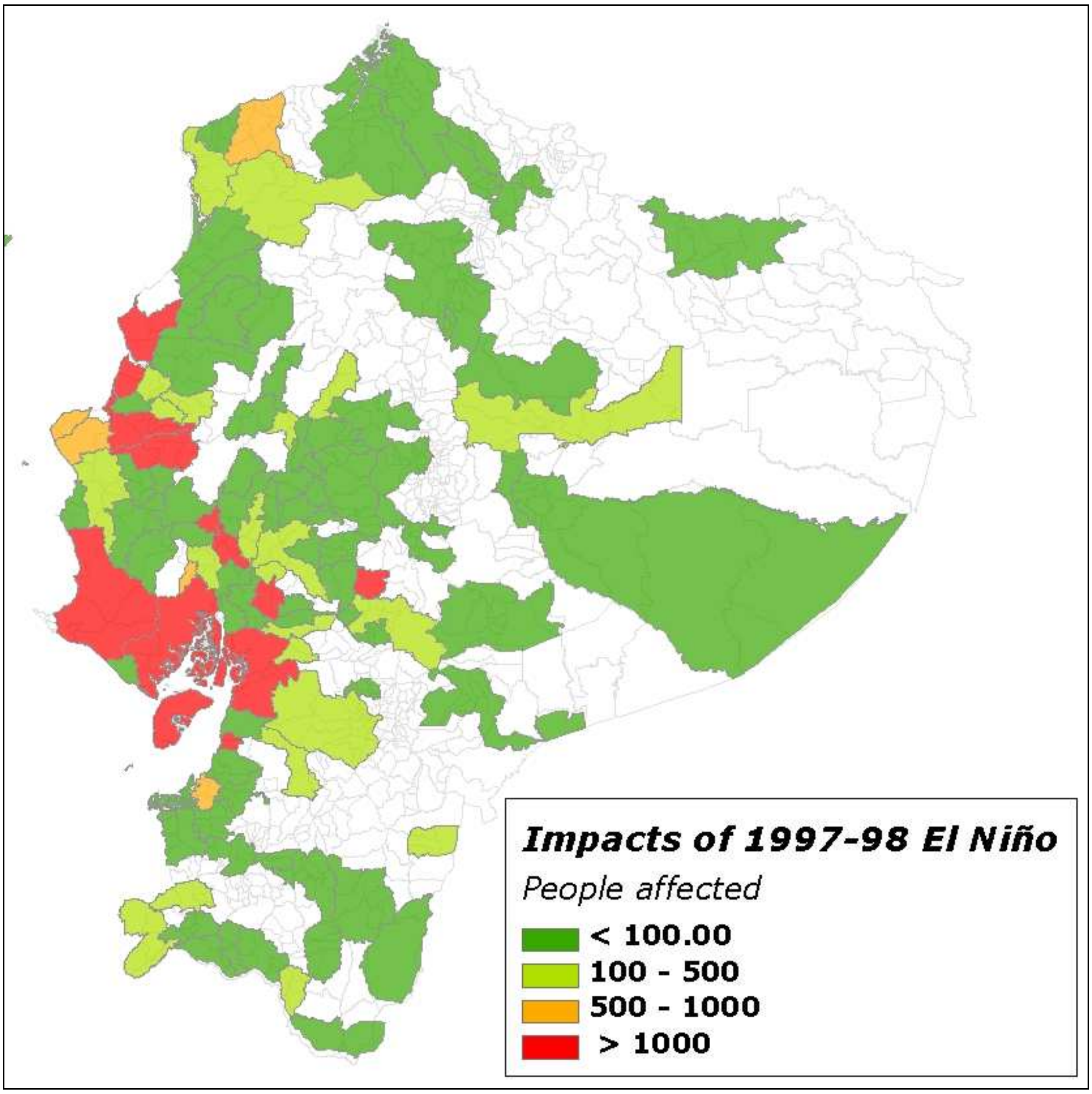

Figure 22. Number of people affected per county reported in DesInventar

However, within the DesInventar data the choice of indicator is critical. For example only 14 counties have data on hectares of crops destroyed, while the number of people and homes affected are reported for almost every county. Each indicator is important for different reasons and an index is required that captures all of the separate indicators without losing the integrity of the original data. Options include an additive index (for instance the number of deaths, wounded, affected) or a multiplicative index (number of people affected multiplied by the number of deaths, etc). I opt for an additive index with three indicators (deaths, wounded, and affected) each indicator having an equal weighting. This is then represented as a proportion of the total population in each county (Figure 23).

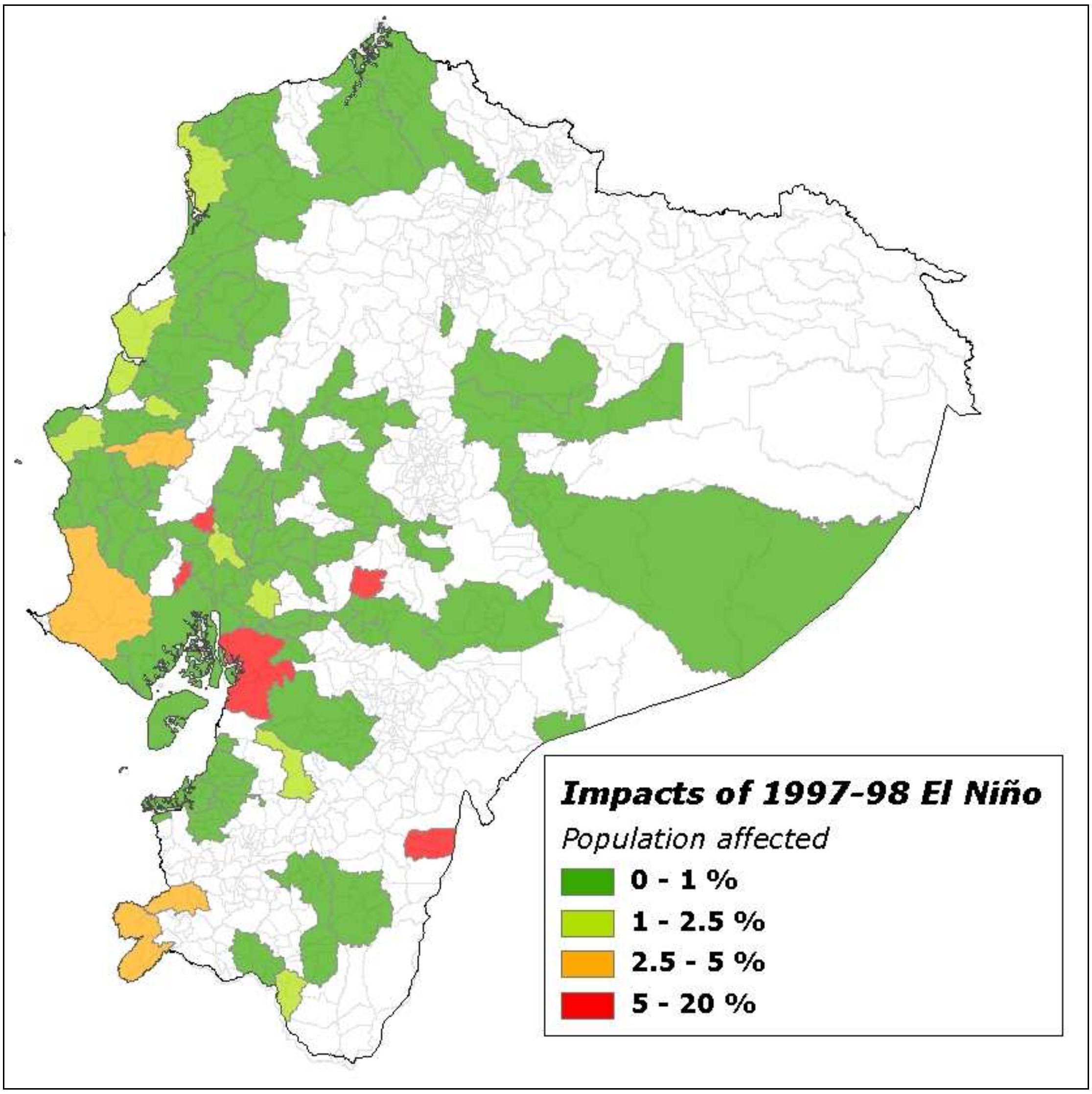

Figure 23. Number of people dead, injured and affected as a percentage of the total population per county reported in DesInventar

3.2.2.2 Maps of exposure

Exposure is an important component of vulnerability and refers to an event which exerts a force on a given population which is exposed. Maps of the exposure to hazardous events associated with previous El Niño events have been produced. These maps do not convey the severity of the event and would need to be analysed in conjunction with maps of population or land use to assess the impact. An analysis of the DesInventar inventory of incident associated with the 1997-98 El Niño event show that the there were two main hazards causing damage. River floods associated with excessive rainfall caused 64% of incidents, while landslides triggered by saturation and run-off caused 23% of incidents.

Maps of flood events can be generated in a number of ways but the most common would be some form of ground survey or more usually via remotely sensed data such as aerial photographs.
Maps showing rivers which were breached during 1997-98 El Niño event and the subsequent flooding are available for Ecuador (Instituto Nacional de Meteorología e Hidrología, 1999 cited in Demoraes and D'Ercole, 2001). Unfortunately the metadata for this source does not contain enough detail to be able to judge the accuracy although a visual assessment of the source suggests the flooded areas were derived from satellite imagery with some cartographic smoothing (Figure 24). A disadvantage of the source is that only large events such as flood plain flooding are captured with any precision. Smaller flash floods in the upper catchments are not captured, neither are landslide events which are numerous but have only localised effects.

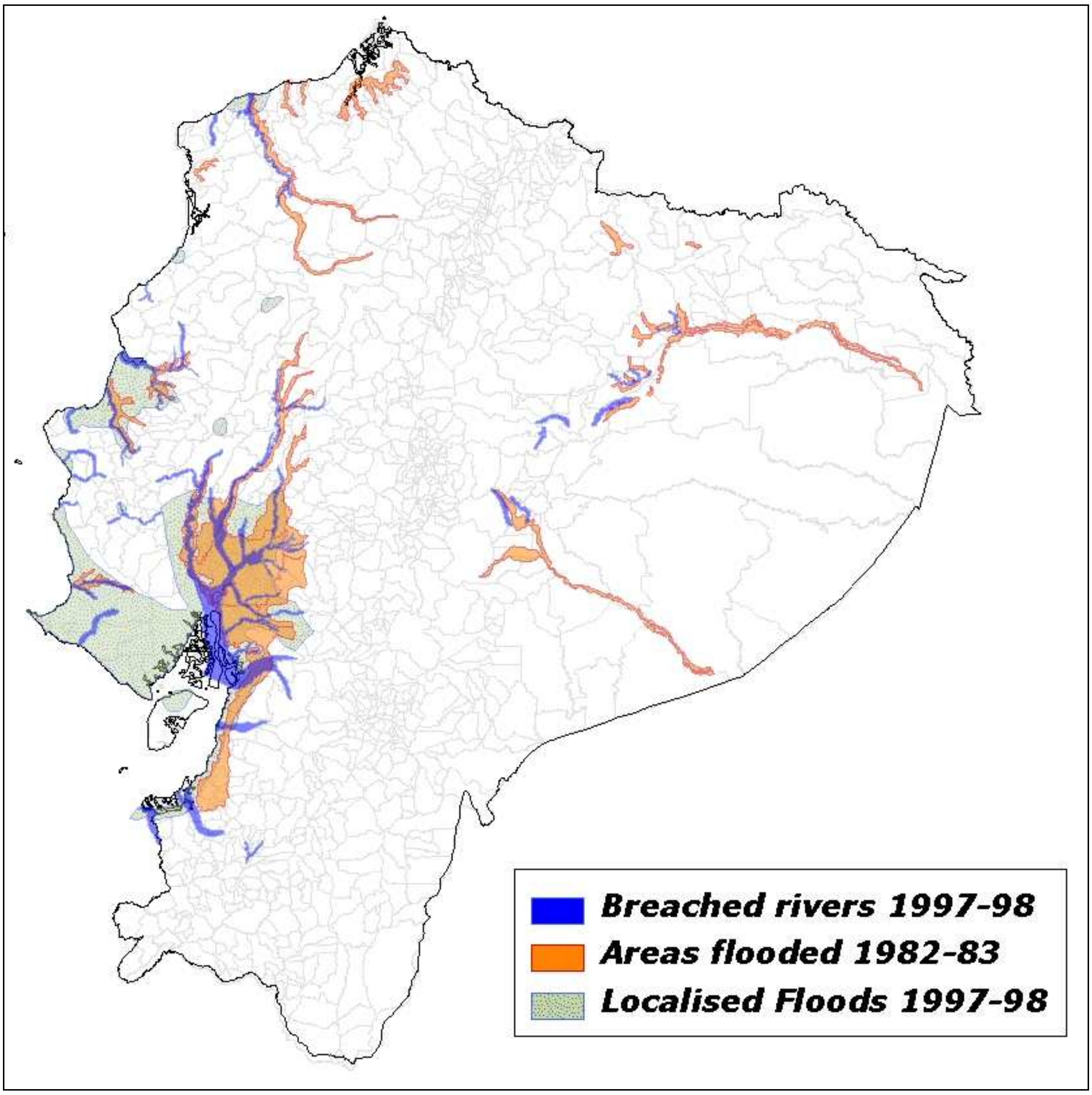

Figure 24. Areas flooded during El Niño events or liable to flood

Landslides and flooding in small catchments can be mapped but these are usually only done for small areas, for example in Figure 25 and Figure 26. These studies are useful for validation purposes but there are too few to be able to assess the impacts of the 1997-98 event at the national scale.

I considered that the information available on exposure to floods and landslides during the 1997-98 El Niño event was not of a high-enough precision to provide a suitable indicator to test against the changes in well-being between 1990 and 2001.

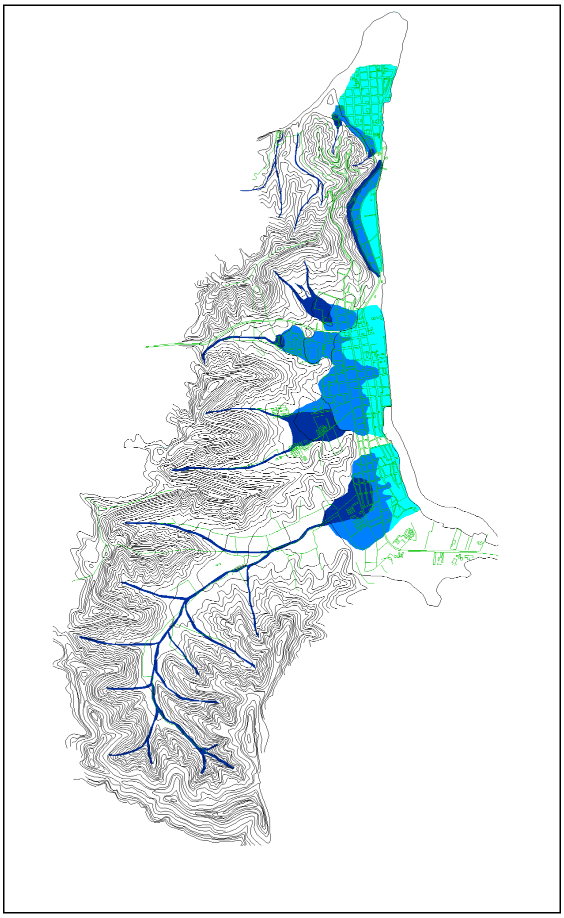

Figure 25. Areas flooded in the town of Bahía de Caráquez in 1998 (Escuela Politécnica Nacional and Dirección Nacional de Defensa Civil, 2000)

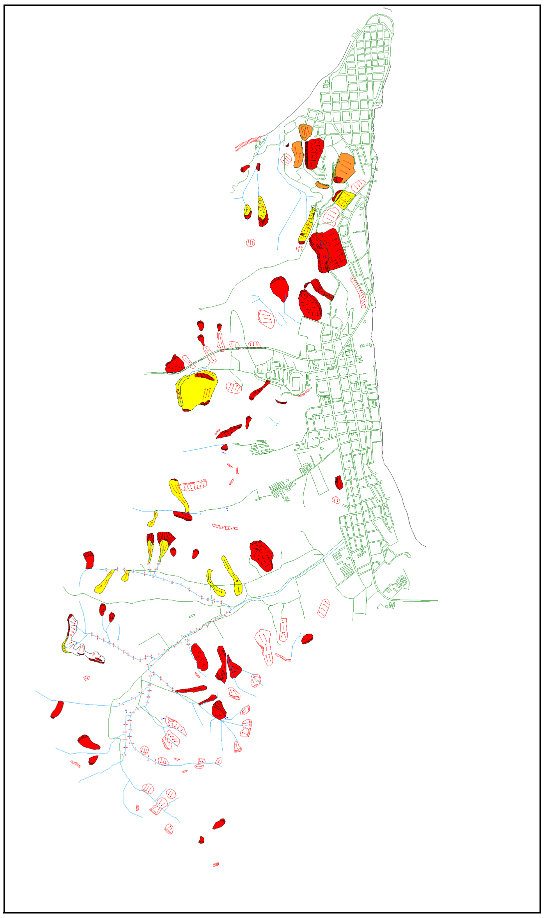

Figure 26. Landslides in the town of Bahía de Caráquez in 1998 (Escuela Politécnica Nacional and Dirección Nacional de Defensa Civil, 2000)

The 1997-98 El Niño event, had a number of direct impacts on Ecuador's weather for over a year between January 1997 and August 1998 (Dirección Nacional de Defensa Civil, 2002; Corporación Andina de Fomento, 2000; Bendix et al., 2002; Bendix and Bendix, 2006). These were heralded by higher sea surface temperatures in the eastern Pacific ocean and were followed in Ecuador by a rise in air temperatures, more cloud cover and an increase in precipitation. Measurements of these values can be compared to non- Niño years and maps of anomalies produced. These anomalies are an alternative way of assessing which areas were most seriously affected. Rainfall anomalies are more relevant than either temperature or solar radiation given that flooding and landslides were responsible for most of the losses associated with El Niño (Vos et al., 1999; DesInventar, 2004).

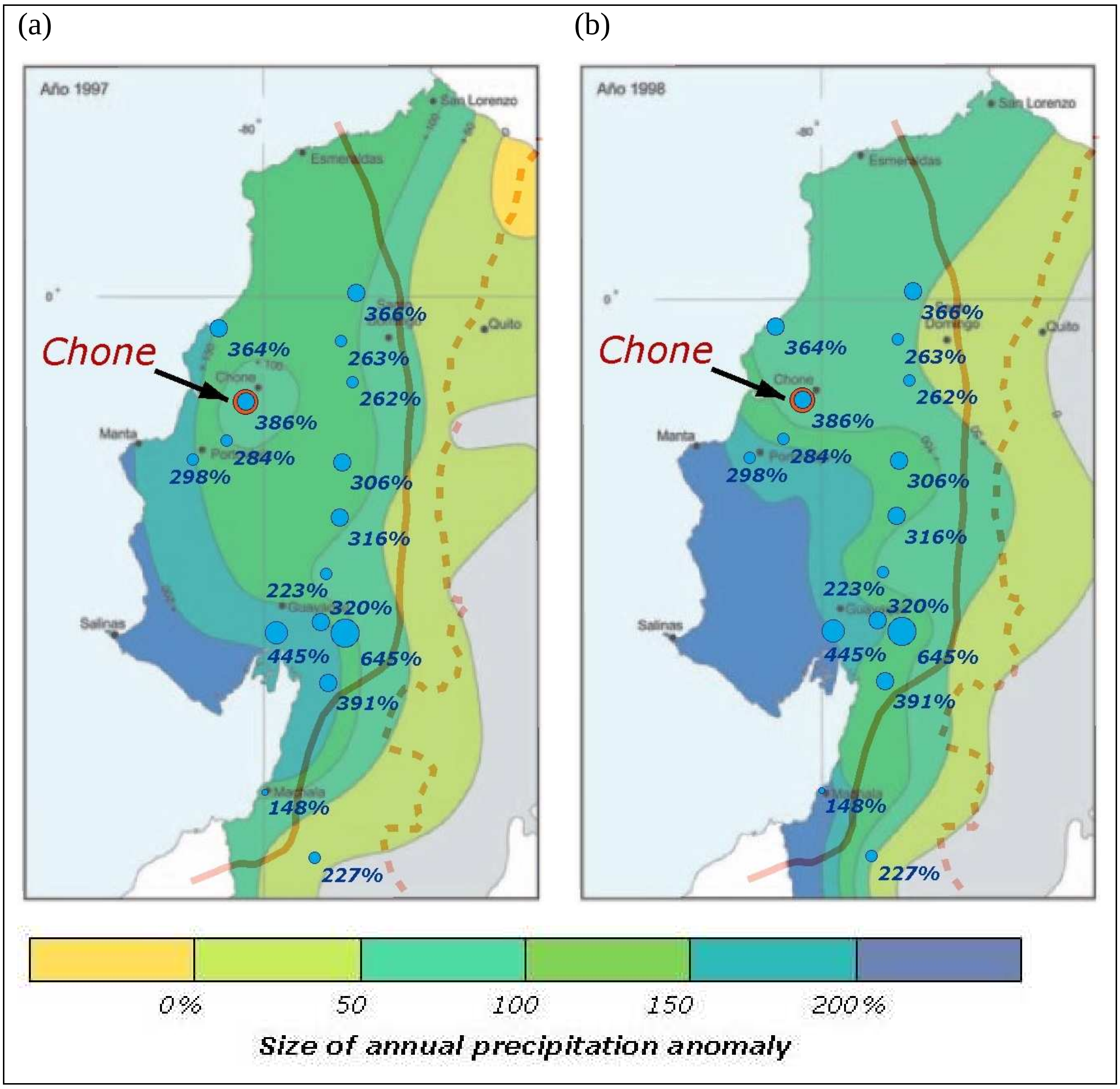

Figure 27. Rainfall anomaly surfaces.

Rainfall anomaly surface for (a) 1997 and (b) 1998, overlaid with anomalies at meteorological stations for period January 1997-July 1998. Limit of direct influence of El Niño (thick line) and indirect influence (broken line) also shown (Instituto Nacional de Meteorología e Hidrología, 1998 cited in Corporación Andina de Fomento, 2000).

Rainfall anomalies have been calculated for all El Nino events between 1965 and 1997-98 (Instituto Nacional de Meteorología e Hidrología, 1998 cited in Corporación Andina de Fomento, 2000; Rossel, 1997). These show slightly differing patterns according to the vagaries of a particular event. The rainfall anomalies for the 1997-98 event are shown in Figure 27. Despite a common source the surfaces do not match exactly the figures for individual stations. This could be explained by the slightly different measuring periods or to the interpolation method used in the creation of the

anomaly surface; these data have been used, however, to define the approximate limits of the direct and indirect influences of El Niño events (Rossel, 1997).
Rainfall anomalies show which areas were exposed to more rainfall than normal but the maps are unable to convey the impact on the ground of the increase in rainfall. In addition these maps mask the shorter-term anomalies which can be seen more clearly in monthly data. Monthly data are unfortunately only available for very few meteorological stations such as Chone (Zevallos, personal communication) in the central coastal province of Manabí (Table 21). Anomalies calculated for shorter time periods, for example weekly or daily are not so powerful given the natural variability in precipitation between different weeks or days in a given year. Data at these precisions allow the identification of extreme precipitation events but are difficult to interpolate over large spatial areas. An alternative to observed data at meteorological stations would be the use of Tropical Rainfall Measuring Mission (TRMM) data such as that used by Bendix et al. (2002).

Table 21. 1997-98 monthly rainfall anomalies (%) for Chone compared to all years 1964-2001 (Asociación COPADE-ICA, n.d.)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1997	41	98	96	139	75	168	222	989	687	577	1716	609
1998	130	109	169	123	285	158	93	1	1	0	86	0

Numerous organisations, including the Ecuadorian civil defence organisation and the *Corporación Andino de Fomento* (CAF), have used maps of anomalies, such as those presented in (Figure 27), to show the area, and thus the districts, directly affected by the 1997-98 El Niño event.
Selecting the districts is subject to a number of sources of uncertainties, primarily the interpolation of anomalies from point observations to large areas lacking meteorological observations, and also a choice as to which rainfall anomaly value to use as the limit of influence for the 1997-98 event.

I have chosen to use the 100% anomaly contours for 1997 and 1998 (Figure 27) as the limits of influence for the 1997-98 El Niño event. The choice is based on the proximity of these anomaly contours to the more general line delineating a direct influence (as opposed to the 50% or 150% contours). The choice of districts changes according to whether the 1997 or 1998 contour is used. I therefore have digitised both contours and chosen districts that are fully within the most-easterly contour or which intersect with the westerly contour to give a dummy variable (Figure 28) for districts that experienced large rainfall anomalies during the 1997-98 El Niño event.

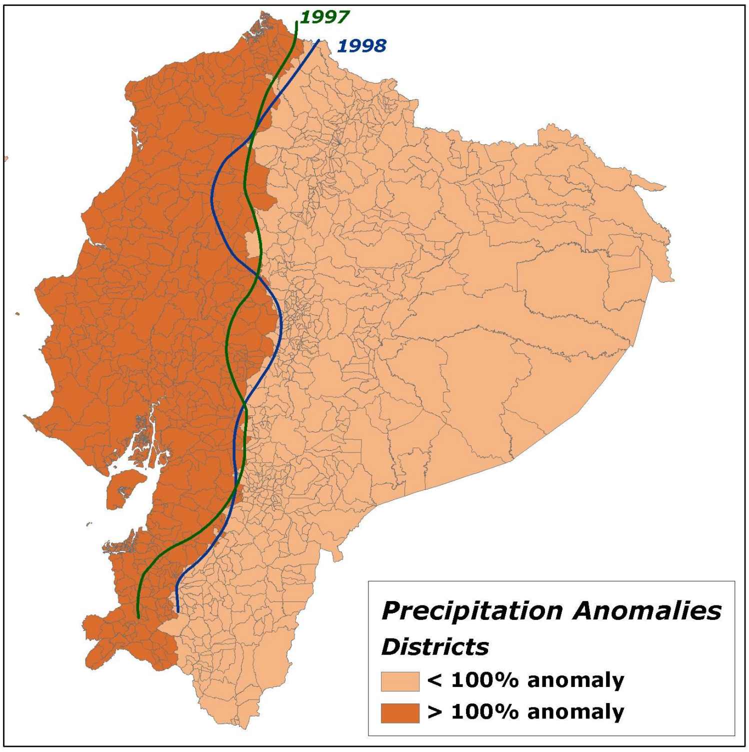

Figure 28. Districts experiencing precipitation anomalies over 100% during 1997 and 1998. Anomaly contours shown for 1997 and 1998 (Instituto Nacional de Meteorología e Hidrología, 1998 cited in Corporación Andina de Fomento, 2000).

3.2.2.3 Assessments of vulnerability or potential exposure to flooding and landslides

Vulnerability assessments take into account the susceptibility of the population potentially affected by flooding or landslides, the drawback in their use is that they do not capture actual incidents of flooding or landslides. Prior to the 1997-98 El Niño event the national civil defence organisation (*Defensa Civil*) produced a list of counties (*cantones*) which were deemed vulnerable to flooding and to damages to the drainage and sewerage systems, including coastal locations which would be at risk from high tides or storm surges (Dirección Nacional de Defensa Civil, 1997 cited in Vos et al., 1999). This assessment, based on the 1982-83 El Niño event identified practically all of the counties in the Coastal region as being vulnerable to flooding, as well as a further 38 counties in the Andean and Amazon regions.

A study in 1998 (Vos et al., 1999) sought to improve on this assessment by concentrating on the risks to losses in the agricultural sector, and on the risks to health. An alternative list and map was produced which identified significantly fewer counties – all except one of these in the Coastal region[37]. This study took poverty levels, land use statistics and data on health services into account and is therefore a useful guide to those communities most likely to be negatively affected by the El Niño phenomenon. The spatial distribution of those counties that are deemed vulnerable to the two impacts by Vos et al., are shown in Figure 29. I shall test both health risk and agricultural loss vulnerability indicators.

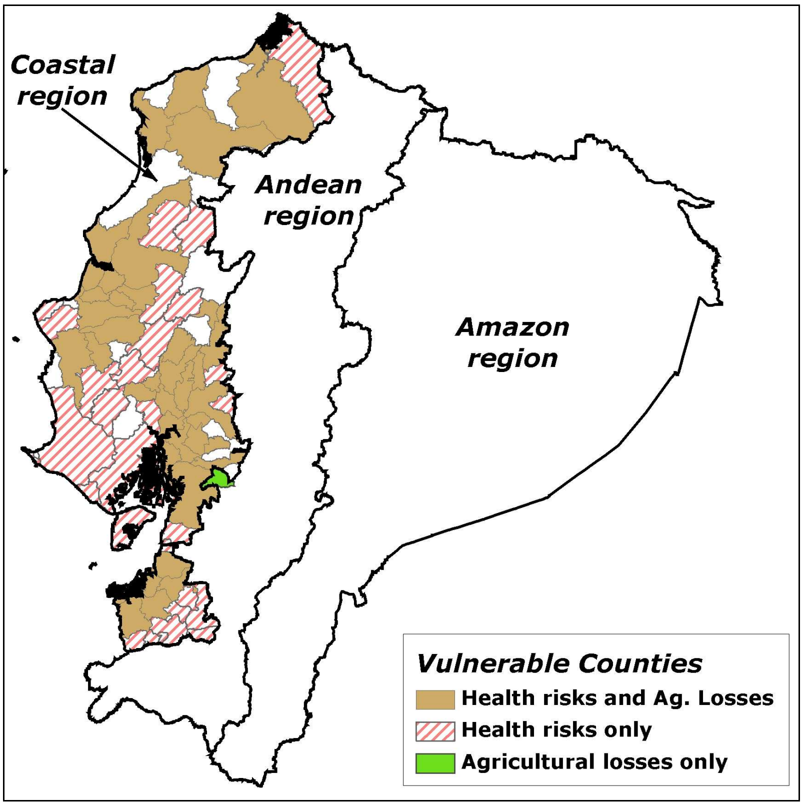

Figure 29. Areas vulnerable to agricultural losses and increased health risks

[37] It is not obvious if the counties from the other regions were included in the vulnerability assessment

3.3 Methods

The hypothesis I wish to test is that there is a positive association between the effects of the 1997-1998 El Niño phenomenon and worsening levels of mean household consumption and poverty at the district level. The implied causal relationship is that the effects of the 1997-98 El Niño event led to lower levels of welfare, all other things being equal. Associations are easier to determine than causality and I rely on the fact that reverse causality (that changes in well-being between 1990 and 2001 contributed to the damaging effects of the 1997-98 El Niño event) is unlikely.

I test the hypothesis using four potential indicators of the effects of the 1997-98 El Niño event:

1) population affected, dead or injured;
2) 1997-98 rainfall anomalies;
3) counties with a population deemed vulnerable to losses in agricultural incomes; and,
4) counties with a population deemed vulnerable to health risks.

Associations are sought with two well-being indicators:

a. Change in z-score of average total consumption per capita per district between 1990 and 2001; and,
b. Change in z-score of poverty headcount ratio per district between 1990 and 2001

I reclassify the consumption, poverty and El Niño data into dichotomous variables in order to construct a number of 2x2 contingency tables on which I will run a χ^2 test. I also test the association with four classes of consumption and poverty z-score change values to produce 4x2 contingency tables of the indicators allowing a more thorough analysis of the differences between the number of cases in each cell of the contingency table and the observed count.

3.4 Results

A summary of the strength of the association between changes in well-being between 1990 and 2001 and four different indicators of the impacts of the 1997-98 El Niño event is shown in Table 22. Contingency tables for each association tested can be viewed in Appendix 5.

Table 22. Summary of χ^2 tests on the associations between changes in well-being and impacts of 1997-98 El Niño event

		Population affected, dead or injured		Rainfall anomalies 1997-98		Vulnerable to losses in agricultural income		Vulnerable to health risks	
		χ^2	P value	χ^2	P value	χ^2	P value	χ^2	P value
Change in consumption z scores 1990-2001	Dummy variable	0.339	0.561	0.156	0.693	0.481	0.488	8.73	<0.01
	reclassified	4.694	0.196	22.251	<0.01	5.364	0.147	35	<0.01
Change in poverty headcount ratio z scores 1990-2001	Dummy variable	26	<0.01	49	<0.01	96	<0.01	171	<0.01
	reclassified	32	<0.01	56	<0.01	105	<0.01	177	<0.01

3.4.1 Association between impacts on well-being and population affected

The first indicator of the impacts of the 1997-98 El Niño event is the population affected, dead or injured as reported in the DesInventar database. The differences between the expected and actual counts in the contingency table are not large for the consumption indicator and a χ^2 test of the association between these two dummy variables is not significant (Table 22). When the change in consumption z-scores is decomposed into four classes the differences between the observed counts and the expected counts have no obvious pattern and if anything would suggest an association contrary to that hypothesised. Unsurprisingly the χ^2 test indicates no significant association between the two variables.

The test of the association between changes in household consumption and the population affected by the impacts of El Niño are repeated for the alternative indicator of household well-being – the change in z-scores of the poverty headcount ratio. The association between these two dummy variables is significant (Table 22); there are more districts than expected with a population affected that have higher z-scores of the poverty headcount ratio. As with the consumption indicator, the dummy variable for poverty can be decomposed to show the degree of change in poverty z-scores. This decomposition shows that the association between the 1997-98 El Niño event and poverty is as expected for all poverty z-score classes and the χ^2 test suggests a highly significant association.

3.4.2 Association between impacts on well-being and 1997-98 rainfall anomalies

Associations between the rainfall anomalies experienced in 1997-98 and the change in district level z-scores of household consumption are contrary to those expected. I find slightly more districts where consumption z-scores have decreased than expected in the areas where rainfall anomalies were smaller, although this association is not significant (Table 22). The decomposition of the dummy variable for z-score of consumption confirms that the association is not strong.

The association between the change in z-scores of the poverty headcount ratio and rainfall anomalies experienced during the 1997-98 El Niño phenomenon is clearer than that seen between rainfall and consumption z-scores. The contingency table shows a strong and significant association between areas that had large rainfall anomalies and those that experienced an increase in the poverty headcount ratio z-score between 1990 and 2001 (Appendix 5, page 338). The association between poverty and the rainfall anomalies that accompany the El Niño phenomenon is just as strong when the change in poverty is decomposed and is still highly significant.
The third indicator of the impacts of the 1997-98 El Niño event is the vulnerability of districts to losses in agricultural income (Vos et al., 1999). Areas were deemed either susceptible or not susceptible to losses, and when combined with poverty indices the districts were classed as either vulnerable or not vulnerable.

3.4.3 Association between impacts on well-being and vulnerability to agricultural losses

The contingency table of the association between the changes in consumption and vulnerable areas (Appendix 5) shows that the differences between expected and actual counts of districts in each cell are very small and that any association is not statistically significant (Table 22). In an effort to obtain more information about a possible association the changes in z-scores of consumption have been reclassified, the association, however, is even less clear.

The differences between expected and observed counts in the contingency table of changes in the poverty z-scores and vulnerability to agricultural losses are greater than those of the change in consumption z-scores and the χ^2 test of the association is highly significant (Table 22). When the poverty dummy variable is split into classes the visual interpretation of the contingency table suggests a slightly weaker association but the χ^2 test of the association is highly significant (Table 22).

3.4.4 Association between impacts on well-being and vulnerability to health risks

The study by Vos et al. (1999) also looked at the vulnerability of households to health risks that accompanied the 1997-98 El Niño event. Districts were deemed either vulnerable or not vulnerable based on the likelihood of epidemics such as malaria or water-borne diseases, and the underlying susceptibility of the population as well as the existence of health services in districts to reduce, and mitigate the effects of epidemics.

An association can be seen between districts which deteriorated between 1990 and 2001 and those districts vulnerable to health risks. This association is significant at the 99% level when using the χ^2 test (Table 22). The changes in consumption can be reclassified in terms of the strength of the change in the z-scores. The pattern seen in the contingency table of the dummy variable is repeated consistently for all classes of changes in consumption z-score. The χ^2 test of the strength of the association between changes in consumption and vulnerability to health risks is again highly significant.

The association between changes in the poverty headcount ratio z-scores and the vulnerability of households to health risks aggregated at the district level is very strong, and as with other indicators is stronger for poverty than for mean values of consumption (Table 22). This association is also evident for the decomposed variable of changes in poverty z-scores. The χ^2 test of the association between change in poverty z-scores and vulnerability to health risks is significant at the 99.9% level.

3.5 Discussion of findings

The association between changes in well-being indicators between 1990 and 2001 and the impacts of the El Niño event have been shown to vary between non-significant and highly positively significant. The results suggest that the choice of indicator is important for both well-being and for the specific impacts caused by the 1997-98 El Niño event. Changes in the z-scores of the poverty headcount ratio is a better indicator of well-being at the district level than mean consumption due to the increasingly unequal distribution of consumption among households in Ecuador (Vos and de Jong, 2000; Hall, 2005).

Changes in the z-scores for consumption present consistently weaker associations than the changes in the poverty headcount ratios z-scores. This is due to the differences in the patterns of change between poverty and mean consumption (Figure 18). Highly *vulnerable* districts tend to show a more significant association with areas whose mean consumption deteriorated during the period 1990-2001 than districts with high per capita recorded instances of impacts.

The differences in the strength of association between the poverty and El Niño indicators are smaller than the differences between the associations between consumption and El Niño indicators. The association is significant or highly significant for every indicator and confirms the idea that poverty is a better choice of well-being indicator.

The analysis of association between poverty z-scores and indicators of the El Niño event is complicated by the length of time between the two well-being indicators. The eleven years that separate the estimates of household consumption are a period of relative stability in Ecuador but as the 1990's drew to a close the political and economic situation in Ecuador became more unstable leading to a crisis in the financial sector and the eventual replacement of the *sucre* as the national currency with the US dollar (World Bank, 2004; Jokisch and Pribilsky, 2002). This may have caused changes in the patterns of well-being during the period 1998-2001, which has an impact on the comparisons of well-being over time. Other potential confounding factors include reconstruction funds to the regions affected by the 1997-98 El Niño event (Comisión Económica para América Latina y el Caribe, 1999[38]) which may have improved the well-being in the areas affected. Alternatively autochthonous reactions to the event such as migration of the worst-hit populations away from the areas affected during the period 1998-2001 could have had an effect on those areas although migration after 1998 was still a more common option in the Andes rather than the Coastal region (Hall, 2005; World Bank 2004).

Similarly the well-being indicators for 1990 may not reflect the pre-El Niño situation although the period between 1990 and 1997 was not as volatile as the period between 1998 and 2001.

Other factors that confound the analysis is that both the poverty headcount ratios and the mean consumption values are based on estimates rather than observed values of household rather consumption (Larrea, 2005; Larrea, 1996) and differences between methods and models can have an impact on the estimates[39].

The analysis in this chapter has shown that there is evidence to support the hypothesis that the 1997-98 El Niño event had a negative effect on household consumption which was manifested as increased poverty headcount ratios at the district level. Areas affected by El Niño experienced greater deterioration in household well-being than other regions of Ecuador, but other macro-economic factors and the long time period between the two data sets make it difficult to isolate the impacts of the 1997-1998 El Niño.

[38] CEPAL note that capital expenditure rose as a proportion of GDP in 1998 due to reconstruction in regions affected by El Niño.

[39] The district level values of poverty headcount ratio differ between those calculated by Larrea (2005) and World Bank econometricians (World Bank, 2004).

The analysis provides some insight into the geographical areas which might experience negative effects in subsequent El Niño events (Figure 17). These insights would need to be augmented with data from a longitudinal survey designed specifically for the purpose of understanding the exact causes of changes in poverty during the period 1990-2001 and the medium-term impacts of the 1997-98 El Niño event. Alternatively an investigation of the perceptions of the causes of changes in well-being should be considered (Figure 4).

The analysis also raises issues about existing assessments of exposure to natural events and the need for improved models of exposure to flood and landslide events that are transparent, modifiable and replicable. This topic is investigated in more detail in the next chapter.

Chapter 4 : District-level exposure to flood and landslide hazards

4.1 Introduction

Many of the negative impacts of the 1997-98 El Niño event were caused by floods and landslides, either directly through the loss of crops and destruction of dwellings, or indirectly through water-borne diseases and blocked roads. The objective of this chapter is to produce and validate a model of exposure to flooding and landslides that corresponds to an extremely strong El Niño event. The chapter will review existing assessments of flooding and mass movements in Ecuador, as well as methods used in other countries to model these. Subsequent sections will describe the construction of models for Ecuador using the most appropriate data and methods for assessing floods and landslides in Ecuador. These are followed by a discussion of the results of the selected methods.

4.1.1 Floods and Landslides

Floods occur when water cannot be transported through run-off channels or via the soil due to stream channels already at their capacity or to soil which is saturated with water and cannot absorb more. Factors associated with floods are precipitation (duration and intensity), the ability of soils to absorb precipitation, the rate at which run-off reaches channels, and the addition of debris that enters channels changing their flow and capacity.

There are also interactions with mass movements of soils and rocks especially in mountainous terrain where landslides can cause the damming of stream channels, the subsequent rupture of these dams causes flash floods which can have severe effects downstream (e.g. Basabe and Bonnard, 2002). There is evidence that the incidence of flooding events, and not just their impact, is increased by changes in land use, such as urbanisation and deforestation (Bradshaw et al., 2007; Nelson and Chomitz, 2007).

The areas affected by floods, especially slower developing flood events associated with the breach of larger rivers, are generally easy to identify and assessments have been directed towards the risk of particular flood events denoted by a return period, e.g. 1 in 20 year flood event (Gumbel, 1941). These assessments have been used for planning purposes and for the design of engineering defences against flood waters (e.g. Basset et al., 2007; Instituto Nacional de Meteorología e Hidrología, 2005). These very defences often only serve to move the flooding from one location to another (Bankoff, 2003) and it becomes clear that floods are not just a natural phenomenon that can be managed using technological interventions.

Landslides are the mass movements of soil and rocks whose spatial extent varies from the slump of a small piece of land to the collapse of half a mountain, and where the rate of movement can be a slow creep over decades, to a rock fall that is over in seconds (Glade and Crozier, 2005).

Landslides are triggered by earthquakes (e.g. Tibaldi et al., 1995), volcanic eruptions (Stillwell, 1992), human disturbances (such as explosions and engineering work), by stream erosion (Bell et al., 2007), by heavy rainfall (Wang, 2005) or a combination of these events. The location, frequency and severity of landslides is more difficult to predict than for floods but there are some factors that will increase the probability of an event, notably the topography, soil and underlying geology and to some extent the amount and type of vegetation cover (Lee and Choi, 2004).

4.1.2 Past assessments in Ecuador

4.1.2.1 Flooding

There have been numerous local assessments of flooding and landslides in Ecuador. The *Defensa Civil*, the body responsible for disaster planning and response, has produced maps of geological and hydrological hazards for a number of urban areas (e.g. Figure 30). These maps are generally not contiguous, and I observe that the methodology used to create these is poorly described, and the source data are not available. As such the accuracy of these assessments is difficult to assess.

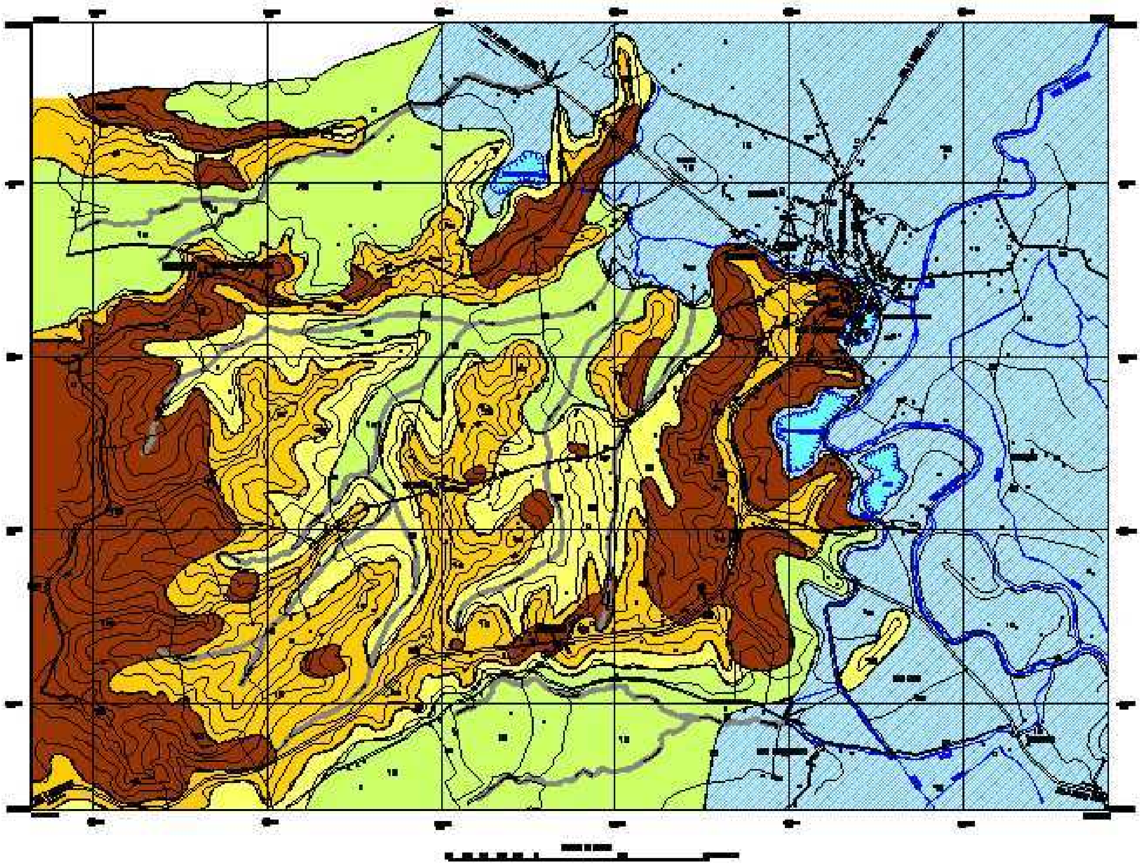

Figure 30. Hazard map prepared for the Defensa Civil for the town of Tosagua, Manabí. Areas in blue are liable to flood; areas in dark brown are susceptible to landslides and mudflows; areas in green are low danger areas; areas in light yellow are of low susceptibility in their current state; areas in orange are of medium danger due to severe soil erosion (Dirección Nacional de Defensa Civil, 2003)

There are national maps of areas that are susceptible to flooding and other hazards which are published as part of the national system of social indicators[40] (SIISE). The maps for flooding are a compilation of (a) areas which have been historically affected by floods, and (b) areas deemed vulnerable to floods (Figure 31). The principal flooding events considered in SIISE were the 1982-83 and the 1997-98 El Niño events. The spatial extent of the 1982-83 flooding is thought by Demoraes and D'Ercole (2001) to be less accurate given a number of conflicting sources, while the 1997-98 event was investigated more systematically by the meteorological and hydrological institute (Instituto Nacional de Meteorología e Hidrología, 1999 cited in Demoraes and D'Ercole, 2001).

[40] Sistema Integrado de Indicadores Sociales del Ecuador (Instituto Nacional de Estadística y Censos, 2008)

The areas that are potentially liable to flood, as opposed to flood occurrences, have been modelled by Demoraes and D'Ercole (2001) as those areas below the 40metre above sea level contour level regardless of the topography or presence of stream channels. The authors themselves recognise the limitations of the method (2001, pg15) although offer little support for the choice of the contour.

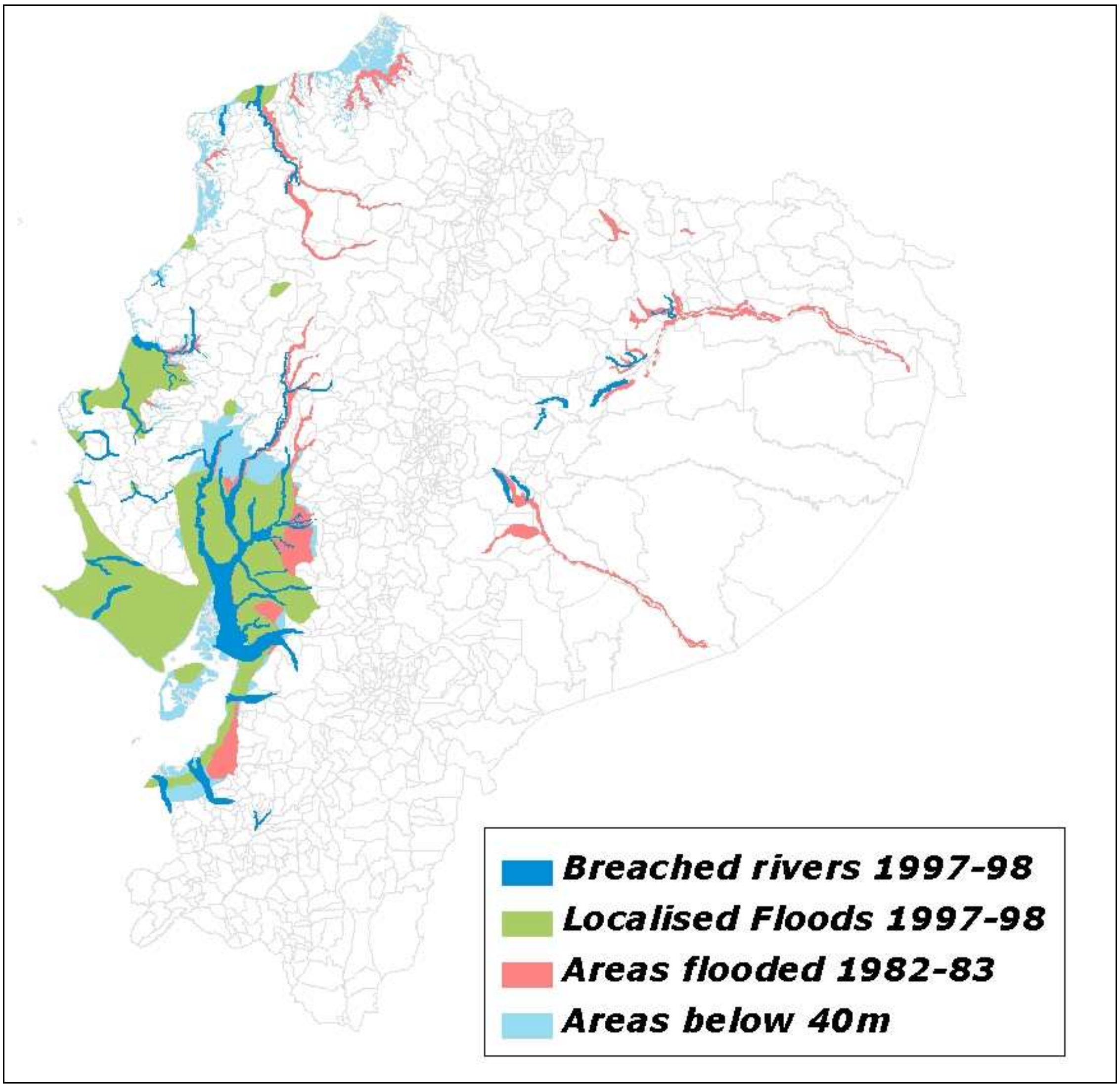

Figure 31. Areas flooded during El Niño events or liable to flood

Another assessment of areas vulnerable to flooding was produced by the national remote sensing centre[41] (CLIRSEN) in association with the council for national security[42] (COSENA). These maps[43] show areas affected in 2002 in the provinces of

[41] Centro de Levantamientos Integrados de Recursos Naturales por Sensores Remotos
[42] Consejo de Seguridad Nacional

Manabí, Los Rios, Guayas and Esmeraldas, as well as areas vulnerable or very vulnerable to flooding. The methodology of this assessment is not given in the maps, although there is some analysis of the impacts of the floods in terms of crops affected as well as the crops in the areas vulnerable to flooding. These appear to have been defined using topographical maps as a base, rather than any previous evaluations of vulnerability. These maps are in digital format but are not publicly available.

There is a further source which shows three categories of flood risk: (1) areas flooded at all times (such as coastal mangrove swamps and parts of the Amazon region); (2) areas liable to flood in every rainy season, and; (3) those areas vulnerable to river breaches and heavy rainfall[44]. The source of these maps is given by DIPECHO as “INAMHI-SIG AGRO MAG” but the same map on the INAMHI website is credited to ODEPLAN, while in a report produced by CAF-SENPLADES (2005) the source is given as “IG-EPN”. The CAF-SENPLADES report suggests that the map has been produced using topographic, meteorological and oceanographic information but no information is provided on the accuracy of the map nor the methods used to create it. This flood risk assessment is not available for the whole country but I have access to subsets of the data for a selection of counties, this source is henceforth referred to as the CAF-SENPLADES assessment.

The assessments described above can be split in two categories; (1) those maps that show observations of areas flooded in particular events, and; (2) areas that are susceptible to flooding under certain conditions and assumptions. The biggest drawback in both cases is the lack of information on the methodologies used to create these maps and assessments of their accuracy.

In addition to the spatial assessments of flooding are databases of events. A comprehensive inventory of flood events has been compiled in the DesInventar database (DesInventar, 2004) (see section 3.2.2.1). The inventory is based on reports of incidents, mainly extracted from national newspapers and dating back to 1960 (Figure 32 and Figure 34). Most incidents in the database include a description of the

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[43] http://www.defensacivil.gov.ec/index.php?option=com_remository&Itemid=83&func=select&id=60

[44] http://ec.europa.eu/echo/pdf_files/calls/dipecho_4_2005/docp_ecuador2005.pdf

events as well as the number of people, households or infrastructure directly affected. Each incident is coded according to the county and a location is recorded but more precise geo-referencing for each incident would require extensive local knowledge of the populated places in each county which is not readily available in Ecuador. A sample of these data is presented in Figure 32.

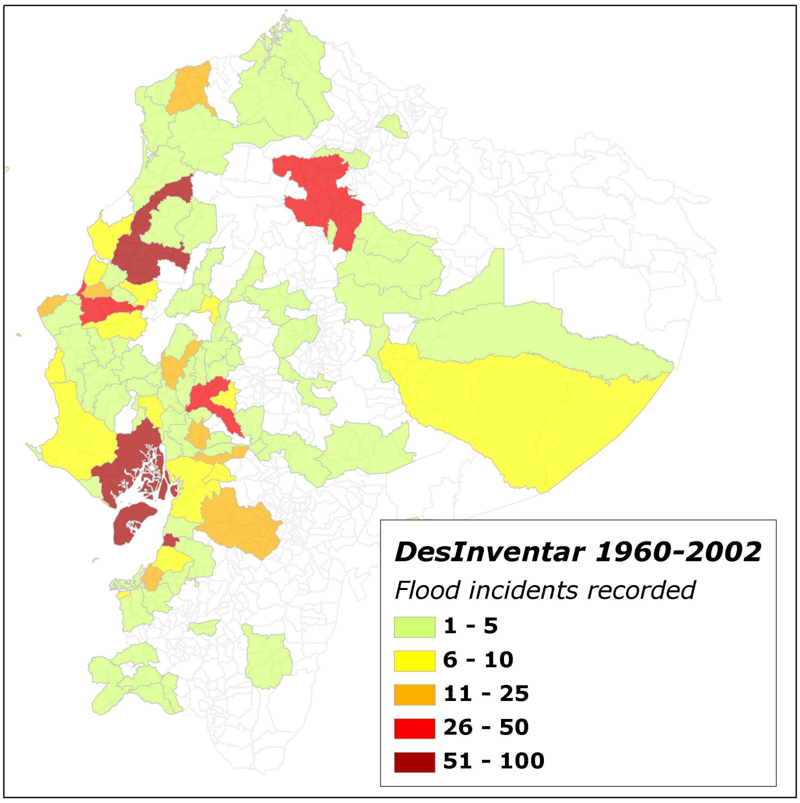


Figure 32. Number of flood incidents reported per county (*canton*) in the DesInventar database between 1960 and 2002

4.1.2.2 Landslides

The only spatially explicit assessment of landslides at the national level in Ecuador was carried out by Demoraes and D'Ercole (2001) and provides a map of landslide risk based on areas deemed susceptible in the INFOPLAN digital atlas and augmented by a map of areas with slopes of over 12° (Souris, 2001)[45]. These areas at risk are based on general geological classifications but there is little metadata to explain the methodology. The authors acknowledge that this is a map of potential for

[45] Slopes derived from 30m resolution DEM created by Marc Souris using 1:25,000, 1:50,000 and 1:100,000 Instituto Geográfico Militar (IGM) Topographic Maps, digitised by MS/IRD/MDMQ

landslides and the result does not entirely coincide with actual occurrences due to the influence of precipitation events such as those associated with the El Niño phenomenon. The authors also recognised that the exact pattern of rainfall can have an influence on landslide occurrence and they give the case for the province of Esmeraldas which suffered many landslides during the 1997-98 El Niño, but few in the 1982-83 El Niño. They go on to mention other factors which are likely to affect the likelihood of experiencing landslides such as the underlying geology, the length of slopes and the amount and type of vegetation cover. The spatially explicit map of landslide potential was subsequently summarised by the authors into an index for each county taking into account the proportion of land area in each county exposed to steep slopes and susceptible geology (Figure 33).

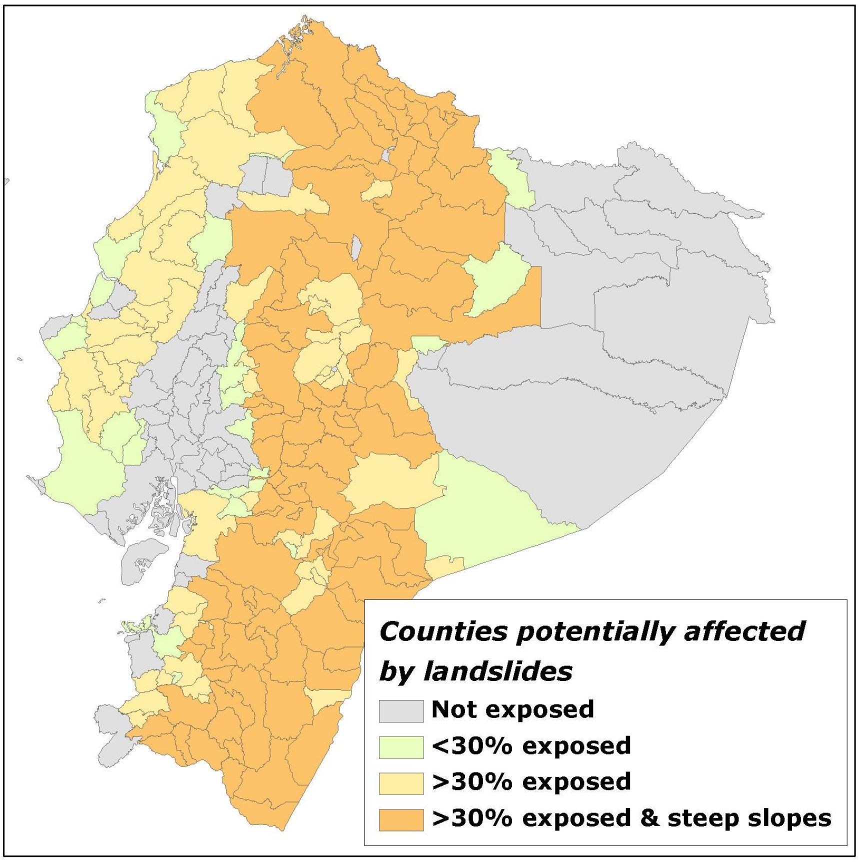


Figure 33. Potential landslide hazard per county (Demoraes and D'Ercole, 2001)

A record of landslide events has also been compiled (Figure 34) in the DesInventar database (DesInventar, 2004), but like the flood events these data are difficult to pinpoint and instead are referenced for each county.

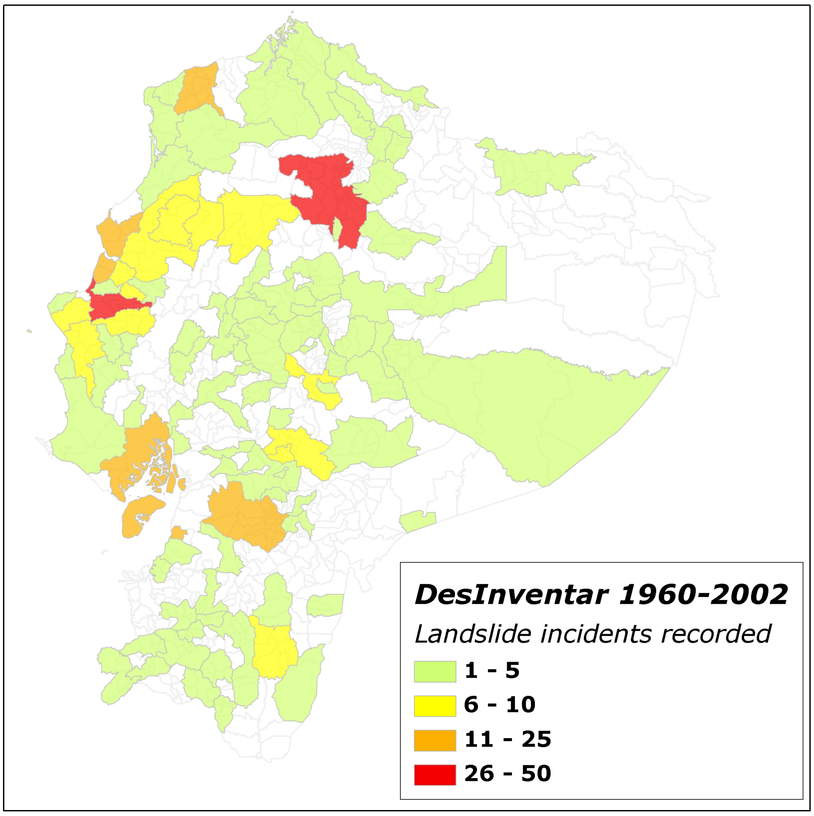


Figure 34. Number of landslide incidents reported per county (*canton*) in the DesInventar database between 1960 and 2002

Apart from these assessments and inventories at the national level there have been numerous studies for specific areas. As with flooding, assessments of actual landslide occurrence and landslide risk have been produced for the Civil Defence institution for localised, generally urban, areas (Figure 30) including 4 zones of the Ecuadorian province of Manabí (Dirección Nacional de Defensa Civil, 2003; Escuela Politécnica Nacional and Dirección Nacional de Defensa Civil, 2000), one of these studies around the coastal town of Bahía de Caráquez (Escuela Politécnica Nacional, and Dirección Nacional de Defensa Civil, 2000) is in an area that appears to have a low risk of landslide events (Demoraes and D'Ercole, 2001) but was severely affected during the 1997-98 El Niño event. These studies of landslide risks concentrate more on the geology than on the soils, and have based their assessment of landslide risks on geotechnical evaluations taking advantage of landslide inventories, local knowledge and primary data capture of sub-soil properties. These assessments produced landslide hazard maps at a scale of 1:10,000, would be difficult to replicate at the national level, and show that the determinants of the different kinds of landslides vary according to location. The only common factor in these studies was the trigger of intense rainfall during rainy seasons and especially the 1982-83 and 1997-98 El Niño events.

In Northern Ecuador Tibaldi et al. (1995) concentrate on a particular seismic event and analyse the distribution of landslides to draw conclusions on the factors determining mass movements and found the most important factor was the interaction of the seismic triggers with fault lines. In the southern Andes of Ecuador Brenning (2005) tests a number of classifiers of the presence or absence of landslides including logistical regression and machine-learning techniques to predict the location of landslide events in a small case study area of $12km^2$. This study validates the classifiers using landslide data from outside the test area as well as the location of 'future' landslides. This study like others above has the advantage of a spatially precise inventory of landslide events from different time periods but provides no detailed information on the co-variates used for landslide prediction. Other studies include the Paute watershed in the eastern cordillera of the Andean region of Ecuador (Basabe and Bonnard, 2002), which focussed on one catastrophic event and implemented a vulnerability assessment in a small area but does not give full details about the most important variables.

The most useful study undertaken in Ecuador for assessing the vulnerability of the population and infrastructure to landslides is that by Demoraes and d'Ercole; this is the only assessment that is national in its scale. There are improvements that could be made however, and it is clear from a comparison of the DesInventar inventory of actual landslide events with the Demoraes and d'Ercole methodology, that the risk of landslides (which considers the triggers of landslides) needs to be considered rather than just the potential[46]. A problem with the method of Demoraes and D'Ercole is that steep slopes are only considered in areas deemed susceptible to erosion due to their geology. The area surrounding Bahía de Caráquez, which has slopes greater than 12°, was not considered susceptible. In addition the authors seem not to have used the highest resolution DEM available from their source data (Souris, 2001).

[46] There is no significant correlation between the number of landslides recorded per county in DesInventar and the potential exposure classes in the Demoraes and D'Ercole study

Slopes derived by the author using a 30 m resolution show large areas with slopes in excess of 12° which do not appear in the maps of Demoraes and D'Ercole. It is therefore assumed that they decreased the resolution of their elevation data in some way. These observations highlight the deficiencies in the description of the methodology used to create the landslide potential map and justify the creation of a new national scale assessment of potential exposure to landslides.

4.1.3 Assessments elsewhere

Future analyses of vulnerability in Ecuador should be informed by efforts in other countries. The geographical extent at which flood and landslide assessments are carried out has a significant bearing on the approach used; in general the larger the extent the simpler the model. The following two sub-sections, therefore, explore the methodologies of national level assessments of flooding and landslides in other countries, as well as drawing on the findings of studies in smaller areas. The availability of data, however, will be a key determinant of the most appropriate methods for landslide and flooding assessments in Ecuador.

4.1.3.1 Flooding

Islam and Sado (2000) use remotely sensed images of flooded areas over a three-week period during a major flood event to determine flood hazards in Bangladesh. The authors do not attempt to model the flow of water across land or along rivers; instead they combine flood frequency and flood depth observations with thematic data on geology, land cover and elevation to rank physiographic units. These units are then aggregated by administrative divisions to provide flood hazard rankings for decision-makers. This method is appropriate for a Bangladeshi context where floods are associated with overflows of large rivers in extremely large catchments in several countries over long durations.

Another national scale assessment, for the Czech Republic (Rodda, 2005), uses a river flow model to analyse the potential damages and insurance claims for different rainfall events. The author uses a 100 m resolution elevation model within a GIS to model areas at risk of flooding given certain rainfall events. Anything above a 1 in 2 year return period flood is counted as a flood event and the author uses river rating curves which allow the conversion of discharge values to water levels.

Van der Bolt and Immerzeel (2002) also propose an integrated model for regional flood risk assessment. The model simulates extreme rainfall events and provides a spatial output showing areas which are flooded. The model – SimGro – uses as input rainfall intensity and location as well as groundwater levels, indeed the model was designed for agricultural water management purposes in a European setting, but the management of surface flow requires information on channel profile, plan and discharge (van Walsum et al., 2005). As a result this may not be the most appropriate model for flood assessments in Ecuador where the topography is a decisive factor in many areas.

Assessments at smaller scales are typically more complex and require a great amount of high resolution spatial and temporal data. For instance vegetation can intercept rainfall, absorb water (Braud et al., 2001) and can decrease both the amount of run-off and the velocity of overland flow (Abrahams et al., 1994; Siepel et al., 2002; Jain et al., 2004), reducing the likelihood of flooding downstream. Changes in vegetation, notably deforestation, have been shown to have a significant effect on frequency and severity of flooding[47] (Bradshaw et al., 2007; Gentry and Lopez-Parodi, 1980); conversely model results of reforestation scenarios show a reduction in discharge and an increase in the lag time between storm events and peak stream discharge (Bahremand et al., 2007).

An example of studies at these scales is provided by Knebl et al. (2005) who couple a rainfall-runoff model with a hydraulic model of stream flow to simulate flood events. Hall et al. (2005) recognise that availability of these data has been a constraint to accurately assess flood risks at the national scale. They show that with advances in national datasets (on topography, land cover, georeferenced socio-economic data, and flood defences) it has become possible to use modelling frameworks that combine statistical, hydraulic and hydrological modelling at large scales to explore management and future climate scenarios. In an Ecuadorian context the data

[47] . However these changes in vegetation have been shown to have an effect on flooding in catchments only up to a size of 50,000 Ha (Chomitz and Kumari, 1998).

available are likely to determine the method I use for assessing the impact of floods associated with El Niño.

4.1.3.2 Landslides

There are few assessments of landslide hazard susceptibility or risk at the national level, and assessments at this scale tend to employ heuristic and qualitative analyses (Glade and Crozier, 2005) matching the complexity of the model with the availability of data. Castellaños (2005) produces a landslide susceptibility map for Cuba based only on 2 topographic variables, maximum slope angle and a measure of 'internal relief'. The second measure gives an indication of the general topography of an area and is measured in the change in elevation per km^2. Castellaños uses the Shuttle Radar Topography Mission (SRTM) elevation dataset as the basis of the topographic indicators but recognises that no triggering mechanisms are considered in the analysis. Reichenbach et al. (2003) also use the SRTM data in their analysis of landslide hazard and risk in Italy; this unpublished study uses climatic, soil and topographic data to predict the absence or presence of landslide occurrences at the municipal scale in any given year. A national level assessment of landslide susceptibility for Germany uses spatial information of slope and lithology but applies expert knowledge in different regions to derive locally relevant classes of susceptibilities (Dikau and Glade, 2003). Guzzetti (2000) attempts to assess the risks (frequency of human deaths) associated with landslides in a national context and shows marked differences in risks between rural and urban as well as between gentle and mountainous districts, however the author acknowledges that cross-national comparisons are difficult given the different triggering mechanisms and susceptibilities. In one of the few assessments of landslide susceptibility at a global scale Hong et al. (2007) include both soil type and soil texture as primary determinants of landslides. The authors make the assumption that coarser and looser soils have a higher susceptibility to landslides, although in the conclusion section they note that areas with soils containing more clay have higher landslide susceptibility.

Studies over smaller areas are almost always based on or validated against inventories of past landslides which offer more options for analysis such as empirical, probabilistic or deterministic models (Glade and Crozier, 2005). Despite the difference in scale these studies offer insights into key variables for predicting landslides as well as modelling frameworks and approaches. Varnes (1984) provides a comprehensive review of early efforts to produce assessments of landslide hazards, recognising the various spatial extents and temporal progression of mass movements and the limitations of the zoning process. The author mentions geology, rather than soil, as a basic condition that contributes to the susceptibility to landslides. However the examples cited by the author show that the contribution of geology is very site specific. Because of the complex relationship between geology, soil and landslides the factors have not been treated consistently in susceptibility assessments. The scale and scope of studies has determined how data on soils and geology have been utilised. Lee and Choi (2004) consider soil texture, drainage, material and thickness in their weights of evidence method for a small study area of $68km^2$. They found that thick, coarse, well drained soils were most susceptible to suffer slides. Soil type (related to lithology) is included as one of five 'natural' factors affecting the likelihood of debris flows in a large study area in central Taiwan (Lu et al., 2007). The authors apply weights to different soils based on their parent material from alluvium (low) to shale (high). Gomez and Kavzoglu (2005) use soil types in their neural net approach to landslide modelling. They give no prior weighting to the soil types but refer to other authors who note that the thickness and cohesiveness of soils is a factor in the likelihood and type of landslides. The authors were not able to derive weights for the contribution of different soil types on landslide susceptibility, a consequence of the neural network approach to landslide susceptibility or prediction (e.g. Wang and Sassa, 2006, or Lee and Evangelista, 2006) used in the study. Baeza and Corominas (2001) include soil type in their multivariate analysis of shallow landslide susceptibility in the eastern Spanish Pyrenees. They include five soil types ranging from colluvium to bedrock in order of their likelihood to fail based on hydraulic conductivity and shear strength. They found however no significant relationship between soil type and landslide susceptibility, which they attribute to the homogeneity of soils within the study area. Larsen and Torres-Sanchez (1998) meanwhile, have difficulty in separating the contribution of soils from other factors such as topography and triggers such as rainfall events which coincide on steep slopes. In their study they do not include soils as a potential contributing factor to landslide occurrence. In contrast Neuhauser and Terhorst (2007) found that soil type and geology were the strongest factors linked with landslide susceptibility in their study of 500km^2 of the Swabian Alb of south-western Germany.

Zaitchik et al. (2003) take a different approach and collect soil samples for their deterministic slope stability model in a 46km^2 study-area in Honduras. Mason and Rosenbaum (2002, cited in Liu et al., 2004) use a combination of geotechnical information derived from field observations and remotely sensed data, and a high resolution digital elevation model derived from stereo-pair aerial photographs. These are combined within a GIS to produce an assessment based on slope instabilities. These techniques follow from Mantovani et al. (1996) who provide a summary of previous studies on landslide hazard assessments. The authors refer to Brabb et al. (1972) who produced a regional scale analysis based on previous landslides, maximum slope angles and the soil parent material. This model was subsequently modified and numerous other factors included in a multivariate analysis which was the precursor for studies that utilise neural networks to produce probabilistic maps of future landslides (Wang and Sassa, 2005) or Bayesian techniques (Lee and Choi, 2004).

Datillo and Spezzano (2003) offer cellular automata as an alternative modelling framework for simulating debris-flows. The size of the cells in this study is 2.5m, and the kind of processes would be difficult to repeat for a country the size of Ecuador. Besides which the purpose of my assessment is not to model flows but rather to assess the propensity of a rather large area (cells of 100*100m) to experience mass movements. In the model I propose each cell would be independent of spatially contiguous cells although in reality there are linkages which could be incorporated by the use of slope curvature variables.

Fabbri et al. (2003) seek to dispel some myths associated with landslide prediction using spatial databases. Most of these myths relate to the quality of the information residing in the spatial database. They show that prediction using multiple datasets in areas ≈ 200 km^2 is not always more effective than a more limited set (for instance just topographic variables). Other studies have also shown that maximum slope angles (between 10° and 30°) are important predictors of landslide occurrences along with soil type/ geology (Neuhäuser and Terhorst, 2007).

Varnes (1984) discusses vegetation as a basic condition that might inhibit the formation of landslides. In particular the author cites Prandini et al. (1977) and notes six factors where forest cover either improves slope stability or can contribute to instability. Specifically vegetation is thought to have a stabilising effect on soils making land less susceptible to mass movements, specifically by reducing pore pressure and increasing cohesion and soil shear strength (Gómez and Kavzoglu, 2005). Larsen and Torres-Sánchez (1998) group land cover classes into three categories based on the differing susceptibility to landslides. The categories range from forest, which is considered as a landslide inhibitor, to developed land or roads which are thought to actively contribute to landslide incidences. In their study in Puerto Rico the authors find a strong relationship between the levels of human disturbance and the incidence of shallow landslides. They attribute this relationship to the impact on soil structure due to compaction as well as increases in shear stress due to undercutting (for instance for road construction) and the dumping of cut materials. Gómez and Kavzoglu (2005) also categorise areas based on the proportion of forest, grassland and bare soils. However the neural net methodology used in the study does not permit an analysis of the contribution of vegetation to landslide susceptibility. Instead there is an assumption, based on previous work by Coppin and Richards (1990) that forests will inhibit shallow landslides while bare soils will aid their formation, an assumption which was confirmed by Lee and Evangelista (2005) in the Philippines.

Other studies and landslide modelling efforts have not been consistent in their treatment of vegetation nor have their results shown a strong relationship between landcover and landslide susceptibility.

Given the scale of my assessment and the likely availability of data in Ecuador a heuristic approach based on a limited set of variables (such as slopes and soils) is the most appropriate to produce maps of within-district susceptibility. Validating this assessment at the national level can only be achieved superficially using the DesInventar database of landslide events (2004) that are referenced for each county.

4.2 Data availability in Ecuador

The availability of suitable input data will be crucial to the production of flood and landslide vulnerability models for Ecuador. In the following sections I describe and provide a critique of the datasets available.

4.2.1 Elevation and topographic data

There are a number of potential sources of elevation data and derivatives in Ecuador. These vary in precision, accuracy, and resolution. The most accurate sources of elevation are those derived from the triangulation network in Ecuador. There are primary and secondary networks of horizontal and vertical control points maintained by Ecuador's national mapping agency the Military Geographical Institute[48]. These data are the basis for all cartography in Ecuador and would form the basis of the most accurate representation of the topography of Ecuador. Unfortunately these control points are not freely available and the costs of digitising contour lines from large-scale cartographic sources made this option infeasible for this study. Alternative sources of relief are derived from remote sensing. The best resolution dataset currently available is elevation data from the National Aeronautics and Space Administration (NASA) Shuttle Radar Topography Mission (SRTM). This is a grid based dataset and each grid cell has a resolution of 3 arc seconds (approximately 92 m at the equator), the vertical error in the original dataset is reported at ± 16 m at the 90% confidence level (USGS, 2006). Jarvis et al. (2004) have shown that the SRTM data are a significant improvement on earlier remotely sensed sources (such as GTOPO30) and elevation models derived from medium scale[49] cartography but that they are inferior to large-scale cartography when using differential GPS as a validation dataset. The SRTM source also has a number of voids (where no data were collected) which have been filled using a number of algorithms and complementary data sources, the vertical root mean square error in the voids varies between 5 m and 20 m[50] (Reuter et al., 2007) when compared with the original SRTM elevation model.

[48] Instituto Geográfico Militar
[49] 1:50,000
[50] Depending on the method used and the topography

Jarvis et al. (2004) show that there are some concerns about using the SRTM for hydrological models due to the large grid cells; however the authors concede that the dataset can be used for basic hydrological modelling.

4.2.2 Hydrological networks

The SRTM elevation grid (with voids filled) is used as the base for the HydroSHEDS[51] suite of data products (Lehner et al., 2006). This dataset has been designed for hydrological modelling at a regional scale and is potentially suitable for analysis at the national scale.
The primary dataset is a hydrologically conditioned elevation model. Depressions and peaks which are thought to be artefacts of the SRTM elevation model are removed, and stream channels are 'burned' into the dataset to a depth of up to 12 m to ensure that flows are maintained along known channels. These burned stream channels are based on ArcWorld (ESRI, 1992) and Global Lakes and Wetlands Database (Lehner and Döll, 2004) and are smoothed using a buffer which is approximately 2.5 kilometres either side of the stream centre-line where burning is 12 m in the centre and 2 m at the edge. These modifications are clear when the hydrologically conditioned elevation model is compared with the original 'void filled' elevation model (Figure 35).
One concern with the use of the HydroSHEDS source is that the data are not projected and as such are unable to be loaded by a number of modelling frameworks (e.g. GeoHEC-HMS). Projecting the hydrologically conditioned elevation model or any of its derivatives requires some re-sampling and inevitably causes the dataset to lose its hydrological integrity.

[51] (Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales)

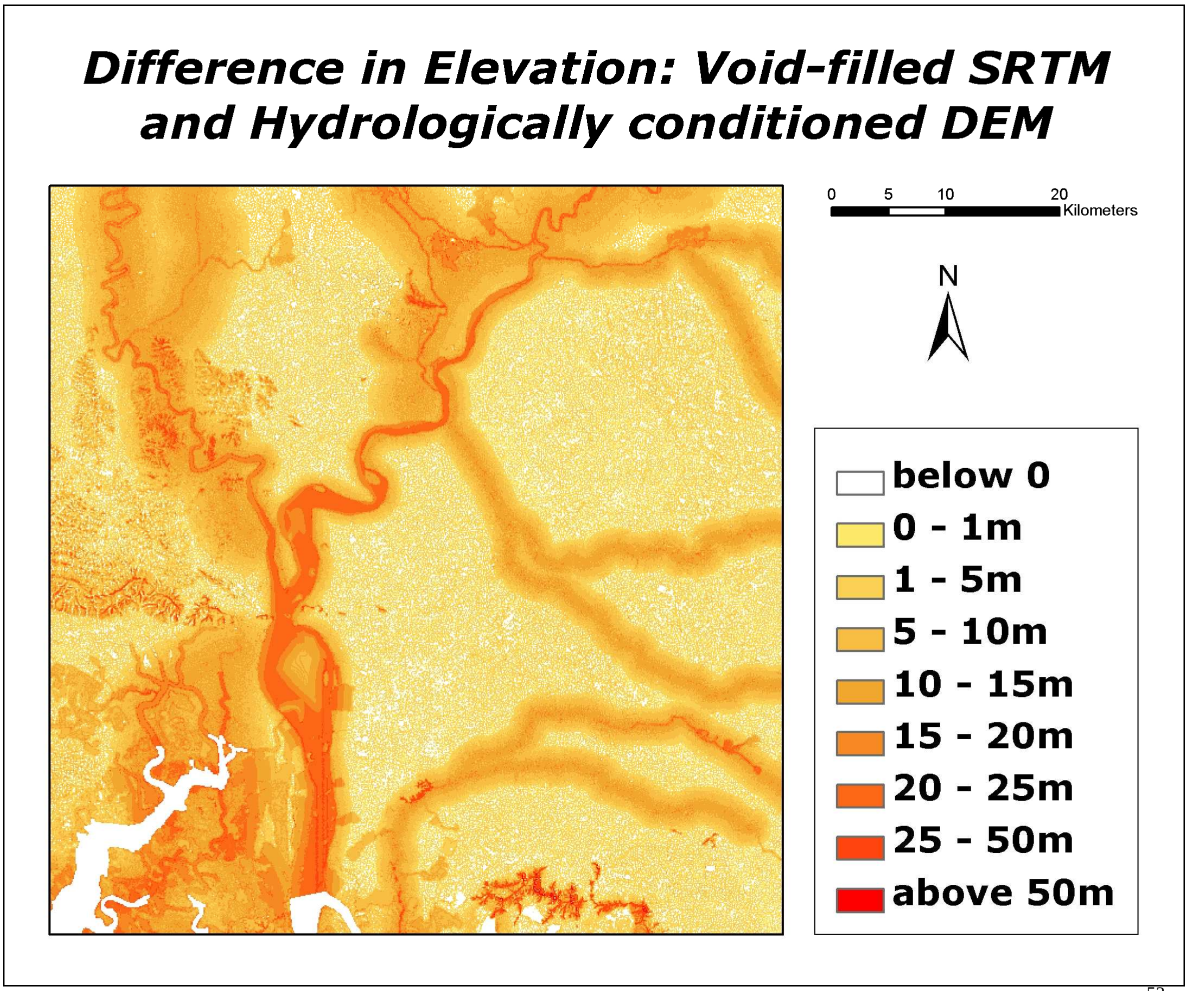


Figure 35. Depth of the burning used to delineate known stream channels in lower Guayas basin[52]

National scale hydrological networks, such as those included in the INFOPLAN digital atlas or the Almanac Atlas of Ecuador (Alianza Jatun Sacha – CDC Ecuador, 2003), are not accompanied by hydrologically-conditioned elevation models. The absence of these complementary datasets limits the application in hydrological modelling. These datasets are of great value however in assessing the location of stream channels derived from or explicitly included in the HydroSHEDS suite of data. Indeed, there are some noticeable differences between the stream channels derived from the hydrologically-conditioned elevation model and those currently in use in Ecuador. These are most severe in areas where there is little variation in elevation (Figure 36), but are reduced in areas where valleys are better defined.

[52] The difference between the hydrologically-conditioned and void filled elevation models is often greater than the 12m burning depth in channels especially in mountainous areas and in low lying areas which are already close to sea level and which are burned deeper than 12m in order to maintain channel integrity and downstream flow.

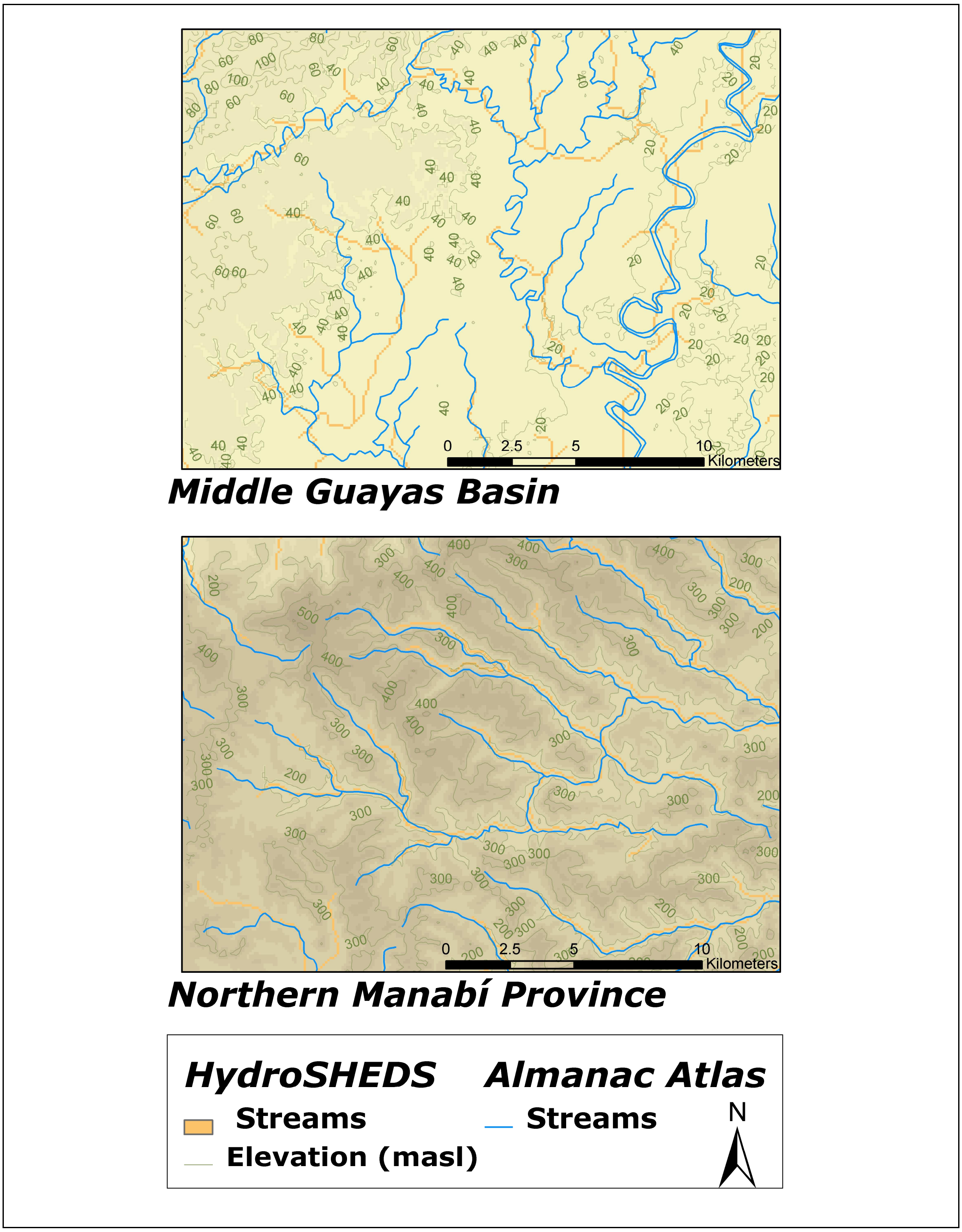


Figure 36. Comparison of stream channels.

Middle Guayas basin and upper reaches of a tributary of the Esmeraldas river in northern Manabí province showing differences between the HydroSHEDS and Almanac Atlas (Alianza Jatun Sacha – CDC Ecuador, 2003) stream channels

These differences in river channel locations in Ecuador are consistent with known deficiencies in the original SRTM elevation data (see section 4.2.1.) used to create the hydrological network, such as the resolution of the sensor, and the confounding of vegetation with ground elevation (Lehner at al, 2006, pg 14).

Despite the modifications to the HydroSHEDS elevation model, the dataset is an improvement on other global or regional scale hydrological datasets – such as HYDRO1k (United States Geological Survey, 2000). Further improvements could be made – and are recommended by the developers of the dataset – with the inclusion of the stream channels from digital atlases of Ecuador in the conditioning of the elevation model; these modifications are beyond the scope of this study however.

4.2.3 Soils and Geology

The best resolution soil data available for the whole of Ecuador are found in a compilation of sources[53] whose original scale varies between 1:500,000 in the Amazon to 1:50,000 in the Andean region (Alianza Jatun Sacha – CDC Ecuador, 2003). This source contains information on the order, sub-order and great group of the soils using the USDA system of soil classification. The source also contains categories of slope, texture, depth, rockiness, drainage, liability to flood, depth of the water table, pH, amount of organic matter, salinity, toxicity, fertility and susceptibility to erosion. The suitability of the soil dataset will depend on a number of factors, many of which are applicable to other digital spatial datasets. Finke (2004) has described seven issues which can be considered: (1) positional quality; (2) attribute quality; (3) completeness; (4) semantic quality; (5) currency (temporal relevance); (6) logical consistency, and; (7) lineage.

[53] See Appendix 6 for details of this source

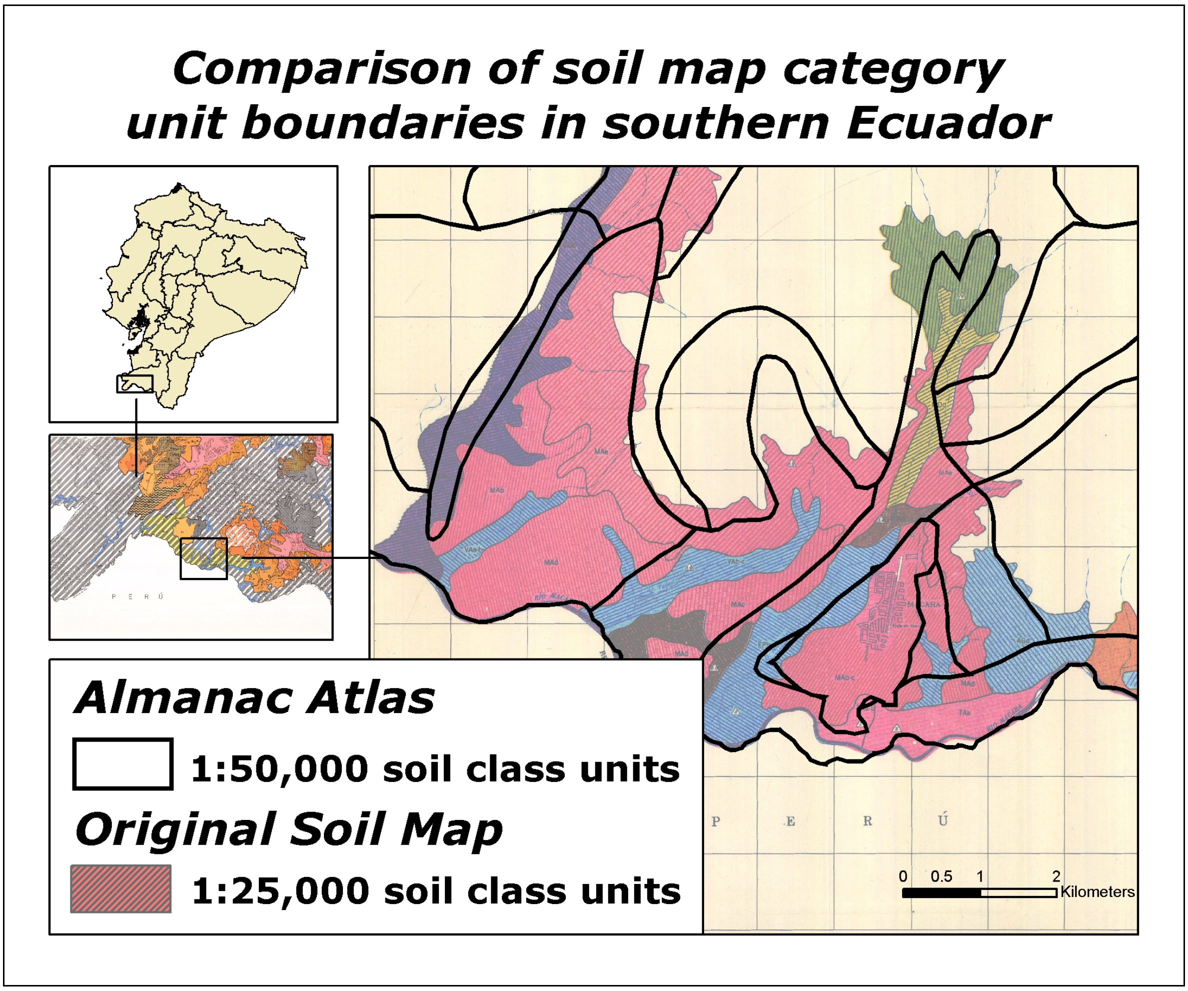


Figure 37. Comparison of soil map boundaries.
Boundaries between the basic soil class units of a 1:25,000 scale sheet (Ministerio de Agricultura y Ganadería, 1974) compared with polygon boundaries of soil units digitised from 1:50,000 soil maps available in the Almanac Atlas of Ecuador (Alianza Jatun Sacha – CDC Ecuador, 2003).

There are often trade-offs between these issues, for instance for the sake of completeness there has been a combination of maps of different ages (currency) and scales (lineage and positional and attribute quality). The positional and attribute quality of the source is not presented although it is possible to compare the national level soil map with larger scale maps for smaller areas. These show that there has been significant generalisation from the larger scale maps to those that were digitised and which form the basis of the soils dataset for Ecuador (Figure 37). The importance of this generalisation on landslide or flood modelling depends to a large degree on the variables of interest and the similarity of the sub-units that have been aggregated.

To give an example, a soil unit classed as an Ustifluvent (fluvent entisol) in the combined soil dataset is comprised of at least 10 units of which 5 predominate (Table 23).

Table 23. Soil units aggregated from 1:25,000 soil map to form one unit in 1:50,000 scale soil map in Macara canton, Loja province in the southern Andes

Code	Sub-group	Texture
Epb	Tropaquent	Sandy over clay
TAa-b	Tropaquent	Loam over mixed loam
TAa	Tropaquent	Loam over mixed loam
Pad	Aquic Ustorthent	Sandy
MDd	Haplustol	Fine clay over fine silt

Even the most detailed vector map representations of soil characteristics used to compile the soils of Ecuador include the “infinitely sharp boundaries” (Lagacherie et al., p 275) between classes and it might be necessary to consider producing more fuzzy boundaries between the soil classes since the boundaries are artificial and the attributes are combinations of smaller units.

4.2.4 Vegetation

A number of land cover or vegetation maps are available for Ecuador. The INFOPLAN digital atlas (Larrea et al., 1999) includes a map of actual land use comprised of 72 classes, which have been grouped into 15 themes, but the source and original scale are unknown and the atlas contains no metadata. An alternative vegetation map (Sierra,1999; Sierra et al., 1999 cited in Sierra et al., 2002) with an original scale of 1:1,000,000 provides a spatial inventory of remaining natural vegetation in 46 classes but defines all other areas as intervened and does not distinguish between different types of agricultural or urban land cover. A more recently published vegetation map features in the Almanac of Ecuador (PROMSA). This has a greater spatial resolution than the INFOPLAN or natural vegetation maps and has been produced from remotely sensed images and other sources from the 1990’s (Alianza Jatun Sacha – CDC Ecuador, 2003). This map has 93 classes and includes both natural, agricultural and urban land cover, as well as combinations of these major classes. The process of constructing this dataset is explained in the metadata; the data were prepared for display at 1:250,000 which has determined the minimum size of the vegetation unit. This map appears to be the best source to use in any landslide or flood models given the high spatial and thematic precision.

Land cover is a dynamic factor changing from season to season and the capacity of vegetation to absorb water will also change during the season (for annual crops). Despite this a ranking of land cover could be devised, going from forest, through pasture, perennial crops (such as bananas) through annual crops to urban areas[54].

4.2.5 River levels and discharge

A comprehensive assessment of river levels and discharge over a suitable length of time is required to provide the ‘ratings curve’ for each river. These curves allow the researcher to assess the discharge that will breach the banks of the river at a particular location. River flow levels and discharge data are also required to validate the storm hydrographs produced by rainfall-runoff models.
Data from stream gauges at the resolution required to validate flood models for particular events are not available in Ecuador (in common with other less developed countries such as Colombia – Poveda et al., 2007). Monthly mean values of level and discharge are available for a limited number of stream gauge locations on some of Ecuador’s larger rivers (Figure 38).

These show that the relationship between discharge and river level is not constant, neither spatially and temporally, due to the differences in the shape of the channel and the longitudinal profile of the reach. Studies of rivers in Ecuador (Instituto Nacional de Meteorología e Hidrología, 2005) have had access to long-term hydrological records and detailed flood plain cross-sections. These studies are very local in nature, however, and are available for very few sites. What is clear is that the likelihood of flooding and the level of the flood do not depend on the discharge, but the impact on the flood plain will be related to the amount of water which overflows the stream banks and is thus related to the discharge.

[54] These could be based on catchment ‘curve numbers, derived empirically in the USA (United States Soil Conservation Service, 1986) for runoff predictions in small catchments.

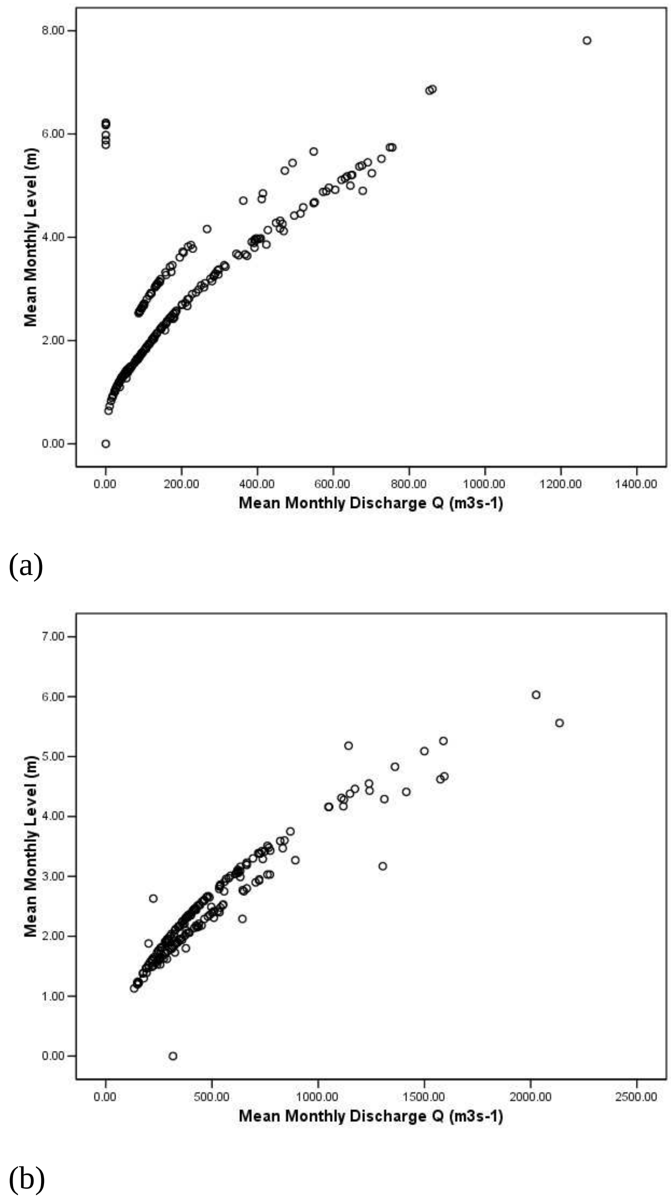


Figure 38. Ratings curves for two rivers in coastal Ecuador. Monthly average flows: (a) Daule (4 m = 400 m^3s^{-1}) and (b) Esmeraldas (4 m = 1,000 m^3s^{-1}) (Instituto Nacional de Meteorología e Hidrología, 2007)

4.2.6 Precipitation

Excessive rainfall, both in duration and intensity is a direct cause of flooding via run-off, and an important trigger of landslides through soil saturation and erosion induced slope instability. This can be seen in the relationships between these events in Ecuador and the incidence of floods and landslides (Figure 39 and Figure 40). The relationship is far from perfect and depends on the rainfall patterns as well as the reporting of the events (see section 3.2.2.1), but does highlight the contribution of excessive rainfall during 1997-98 El Niño event.

Precipitation data are more commonly used for simulation and early-warning of flooding (e.g. Toth et al., 2000) or landslides rather than for assessments of exposure or susceptibility. This is because precipitation is more dynamic and stochastic than other factors that contribute to susceptibility such as slope, drainage patterns and geology.

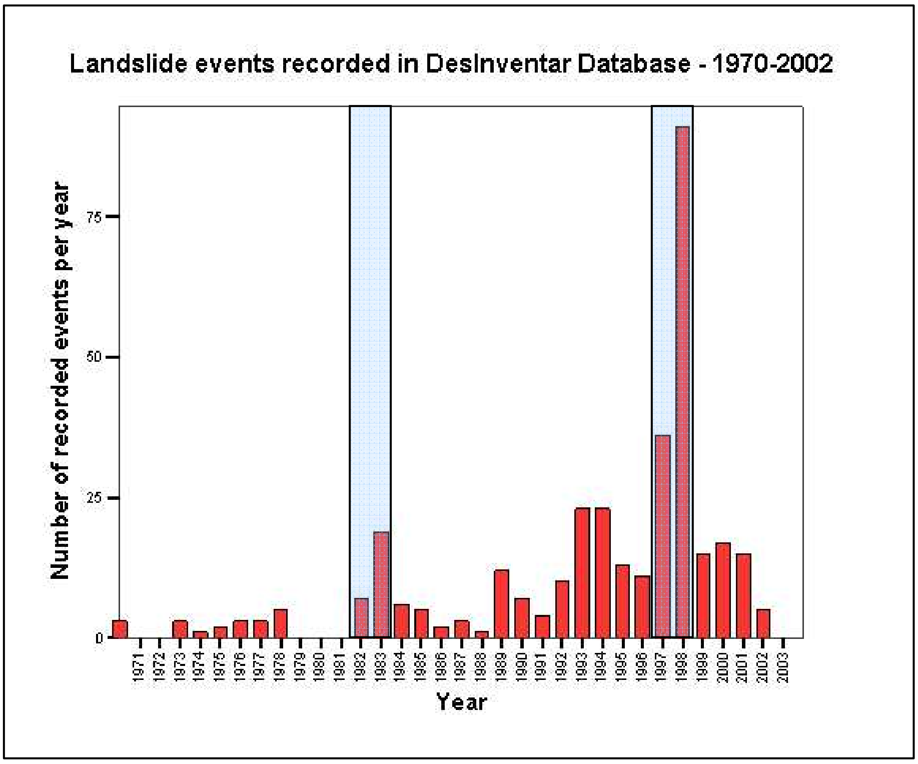


Figure 39. Landslide events recorded in DesInventar database 1970-2002.
Frequency of reported events with extremely strong El Niño events highlighted in blue (DesInventar, 2004)

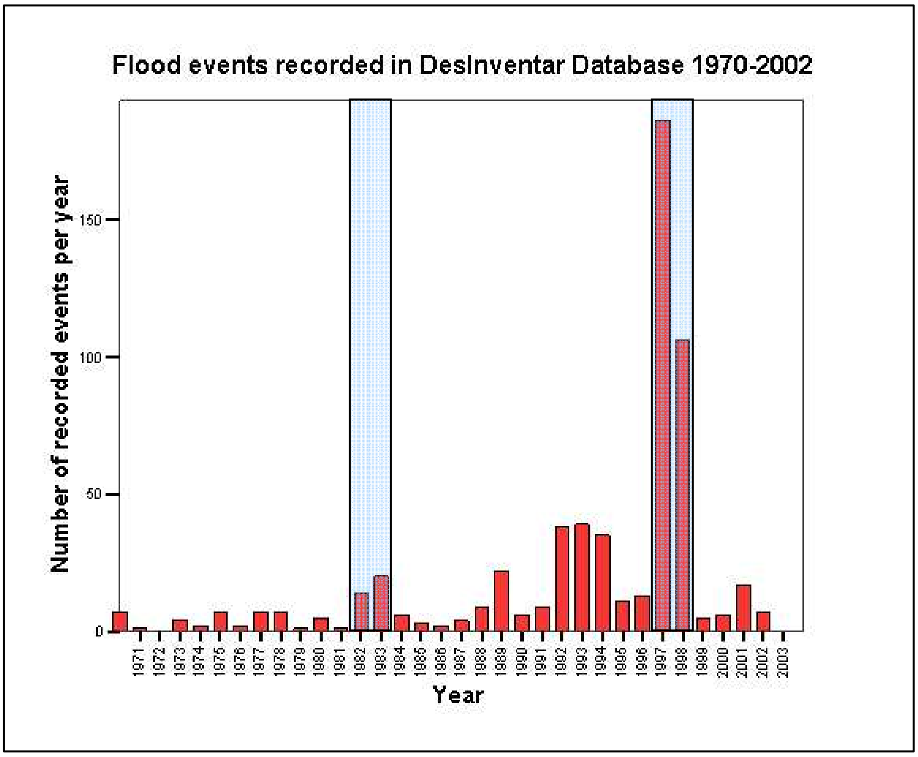


Figure 40. Flood events recorded in DesInventar database 1970-2002.
Frequency of reported events with extremely strong El Niño events highlighted in blue (DesInventar, 2004)

Monthly averages of precipitation are available globally (Hijmans et al., 2005) at a resolution of 1 km (Figure 41) but these capture neither the intense rainfall events in a normal year, nor the extremely large inter-annual differences.

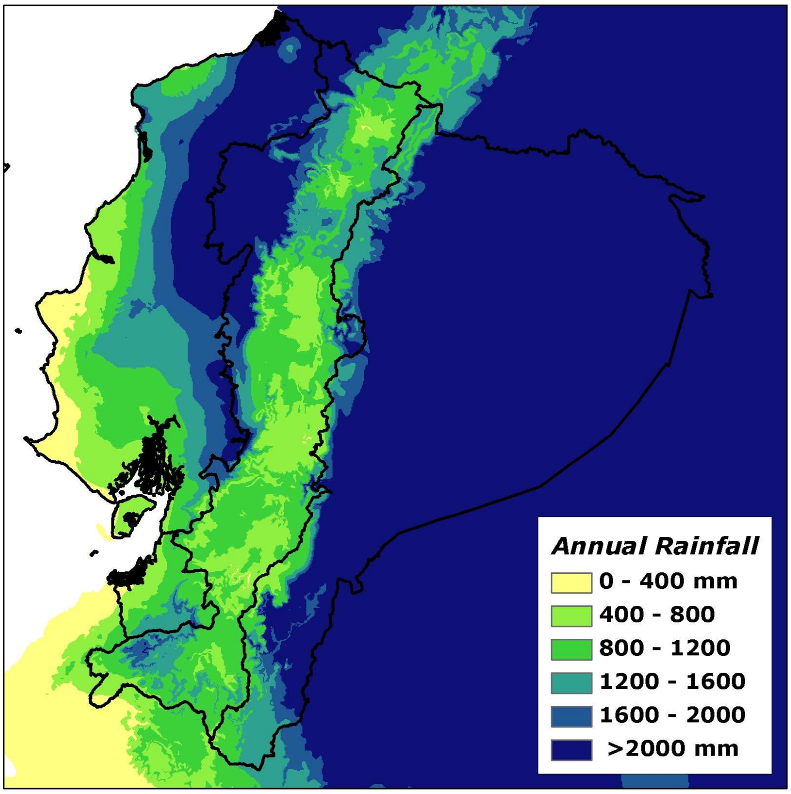


Figure 41. Annual rainfall in Ecuador

Rainfall data from meteorological stations are the most accurate source of information and records are often maintained for decades. The spatial distribution of these stations however is often not sufficient for modelling frameworks (see section 3.2.2.2) so interpolation is required. An alternative to interpolation is to use satellite based sensors to monitor cloud cover and estimate rainfall according to cloud characteristics. An example is the Tropical Rainfall Measuring Mission (TRMM) (NASA, 2008; Simpson et al., 1996) which was launched in November 1997. The relationship between these data and ground observations is variable but these data have been used in hydrological modelling (e.g. Artan et al., 2007).

Given the importance of the El Niño event for both landslide and flooding incidents there is great value in understanding spatial variability and the differences in precipitation between El Niño and non-El Niño years. Section 3.2.2.2 discusses in detail temporal rainfall anomalies. Monthly data for specific years are available for a limited number of meteorological stations situated in the coastal province of Manabí and previous studies have derived maps of rainfall anomalies (Table 21).

4.3 Methods

4.3.1 Flood model

Despite the various assessments of floods in Ecuador there has been an improvement over the past five years in the data that are available. As a result it should be possible for this research to construct a model that better identifies areas liable to flooding, according to different rainfall scenarios. In addition it is necessary to determine the costs of those flood events or at least estimate the population affected by flooding and produce a rank of districts according to different rainfall events, so that resources can be directed to reduce negative impacts.

4.3.1.1 An ideal flood model

The ideal model would be spatially and temporally explicit with prior information on water in the system in streams, soil and as groundwater. Precipitation would need to be simulated at regular intervals, and distributed spatially. The interception and evapo-transpiration would be modelled according to the vegetation and the remainder of the water modelled as overland, subsurface and groundwater flow (Beven and Kirby, 1979).

The modelling of these flows would be based on a hydrologically correct elevation model with artificial sinks removed and natural sinks revised. The stream channel locations and their dimensions would be known at all points. In addition it would be necessary to take into account any structures designed to control floods, or barriers such as bridges or culverts that could cause floods. Hydraulic models would be used to estimate the depth and velocity of stream flows in order to identify the locations of the overflow of stream channels and subsequent flooding. The floodplain topography would determine the depth and area of floods which would be used in conjunction with databases on buildings, infrastructure and agriculture to assess physical damages. Aggregate values would then be calculated for each district.

4.3.1.2 Constraints to producing an ideal model

The constraints to realising this deterministic modelling framework are threefold: (1) availability of, and access to, data; (2) modelling tools (software), and; (3) processing and storage capacity (hardware).

Section 4.2 above outlines the data available for the whole of Ecuador for key data sets and it is obvious that due to a lack of data at the necessary resolution the ideal model cannot be achieved. Rainfall-runoff hydrological models require simulated rainfall data at high temporal resolution. Daily rainfall estimates at a resolution of 0.25º x 0.25º for the period post 1997 are available using TRMM estimates but the computing processing power required for modelling such a large area are unavailable for this study. A simpler approach is needed which makes best use of the available data. The most important dataset available is the HydroSHEDS data which provides a hydrologically correct elevation model. Information on the upstream area at any particular location can be derived using these data. This upstream area needs to be converted into discharge and to flood elevation and thence to areas flooded. Power laws (Gupta and Waymire, 2000, cited in Poveda et al., 2007) are commonly used for relating basin area to mean and maximum flows, these relationships are often specific to a particular catchment. This can be seen from the monthly mean and monthly maximum discharge values for selected rivers in Ecuador (Table 24). The rivers with the greatest average discharge per km^2 tend to be located in the upper reaches of the catchments but there are notable differences between the relationships of mean and maximum discharge values to upstream area. These relationships will depend on the precipitation regime in the upstream area as well as interception of precipitation by vegetation, and evaporation.

Table 24. Comparison of discharge and catchment areas for gauges on selected rivers in Ecuador

		Upstream Area (Catchment)			Average monthly discharge (Q) m^3s^{-1}			
Gauge	n (months)	Area km^2	Rainfall mm/yr	Slope º	Qmean	Qmax	Qmean/km^2	Qmax/km^2
Carrizal	343	521	1460	14	12.648	105.026	0.024	0.201
Daule	246	9037	1767	6	208.402	1268.473	0.023	0.140
Esmeraldas	213	19470	1992	12	638.320	2135.829	0.033	0.110
Zapotal	380	2621	1665	14	137.844	665.216	0.053	0.254
Mira	357	4983	1183	17	146.129	389.933	0.029	0.078
Toachi	411	2135	1444	19	44.764	267.792	0.021	0.125
Pindo	463	507	1177	20	23.860	103.972	0.047	0.205
Puyango	474	2687	1330	19	84.626	462.002	0.031	0.172
Uchima	369	135	1052	24	3.036	49.299	0.023	0.366
Cebadas	277	1302	684	15	20.643	99.169	0.016	0.076
Tomebamba	445	1266	901	14	17.057	79.681	0.013	0.063

An ordinary least squares linear regression model was calibrated to explore the relationships between flow accumulation, mean slope and mean annual rainfall on the mean discharge at these 11 river gauge locations. The model fit was very high with an adjusted r^2 of 0.968 but the only significant explanatory variable was the upstream area (Table 25).

Table 25. Summary of model calibration of mean monthly discharge for gauges on selected rivers in Ecuador

Explanatory variable	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
Upstream area (catchment)	B	Std. Error	Beta		
(Constant)	-121.722	70.772		-1.720	0.129
Slope º	4.111	2.634	0.106	1.561	0.163
Rainfall mm/yr	0.037	0.039	0.077	0.951	0.373
Upstream area (gridcells)	<0.01	<0.01	0.987	11.699	<0.01

n=11; y = mean monthly discharge

The interaction between rainfall, slope and catchment area is complicated, although when a new variable – rainfall * catchment area - is introduced there is a very slight improvement in the model fit with the adjusted r^2 rising to 0.970.

Catchments can be summarised using standardised 'curve' numbers which are empirical relationships based on observations of average runoff in a large number of small catchments (United States Soil Conservation Service, 1986). The curve numbers are used to modify the relationship between the characteristics of catchments and the discharge of rivers. Standardised curve numbers for different vegetation types and soil hydrological properties do not exist for Ecuador but they can be created using a combination of the vegetation and soil maps available for Ecuador. While curve numbers are a useful guide to the effect of soil and vegetation on runoff and ultimately discharge they are only practical for use in small homogeneous catchments and for specific precipitation events (United States Soil Conservation Service, 1986). Nevertheless the raw curve numbers are included in the simple model to predict mean monthly discharge at the available river gauges. The inclusion of the raw curve numbers does not improve the model calibration[55] and the variable is not significant.

Table 26. Summary of model calibration of mean monthly discharge for gauges on selected rivers in Ecuador

Explanatory variable	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
Upstream area (catchment)	B	Std. Error	Beta		
(Constant)	-7.196	12.951		-0.556	0.592
Upstream area (gridcells)	0.00027	0.000	0.984	16.642	<0.01

n=11; y = mean monthly discharge

Given these findings and due to the theoretical difficulties of applying US curve numbers to Ecuadorian land cover classes I will make the assumption that discharge is proportional to area using the coefficients from a linear regression model with upstream area as the only explanatory variable (Table 26). This decision is also based on the fact that the El Niño event was of a long duration and I will not be modelling individual rainfall events (which might arise from storm cells smaller in size than large catchments [Sólyom and Tucker, 2007]).

4.3.1.3 Flood model for Ecuador

Since very few stream sections have published ratings curves relating discharge with flood levels I will have to make assumptions about these relationships. However an analysis of the channel level and discharge for published gauges (e.g. Figure 38) using curve fitting algorithms can give some insights into the relationship. Curves were fitted to the data selecting power functions of the form

$$\text{Level} = a * \text{Discharge}^b$$

Where a and b are constants

The results (Table 27) display a range of coefficients but the average value for the b coefficient is close to 0.5 which suggests an inverse quadratic relationship between

[55] r^2 of 0.968

mean monthly discharge and mean monthly level. The flood levels, however, are difficult to discern from these curves without data from the flood events rather than the mean monthly flows.

Table 27. Relationship between mean monthly river level and discharge at selected river gauges between 1962 and 2005

Gauge	n	R^2	a	b
Carrizal	328	0.711		0.277
Daule	239	0.928	0.201	0.505
Esmeraldas	211	0.947	0.065	0.592
Zapotal	354	0.687	0.048	0.670
Mira	356	0.953	0.109	0.542
Toachi	411	0.914	0.218	0.580
Pindo	402	0.859	0.055	0.756
Puyango	438	0.958	0.039	0.751
Uchima	221	0.940	0.556	0.343
Cebadas	276	0.961	0.646	0.250
Tomebamba	414	0.863	0.164	0.514

The flood level and the discharge will also determine the area of the floodplain adjacent to the stream which is flooded. In this model I will assume that the area liable to flood is determined by the difference in elevation between upstream cells and the stream flood elevation. Both upstream and stream cells are based on the HydroSHEDS hydrologically conditioned elevation model which has a resolution of approximately 92 metres. The upstream cells for each stream section are identified and given the same elevation value as the stream (Rodda, 2005) the flood level is added to the new elevation grid and if the new grid is higher than the original elevation the cell is deemed to have flooded. In areas of gentle terrain it will be necessary to place limits on the distance the flood waters can travel and buffers can be included in the model at distances relative to the discharge or upstream area. This is repeated for each flood level and the flood areas are merged. Any areas below sea level (due to burning during HydroSHEDS development) are given a value of 0 metres above sea level. Different flood levels are given based on the assumption that discharge is relative to upstream area based on the relationships observed between flow accumulation and discharge (Table 26) and on the relationships between discharge and flood level (Table 27).

This gives the formula[56]:

Flood Level = a * Discharge^b

Where a = 0.2 ; b = 0.5
and Discharge = -7.196135279937 + 0.0002684280988779 * upstream area

This results in a maximum flood level of 11.9 metres which is a reasonable value for the largest rivers but the formula does not give values for streams with an upstream area less than 26,808 grid cells (or approximately 227km^2).

Given this I have decided to simplify the model to a simple relationship between flood level and flow accumulation where the maximum flood level encountered is 10 metres. Rather than apply the formula to every grid cell in the flow accumulation grid (which is potentially computationally intensive) I have decided to split the streams into different sizes based on their upstream area. A maximum flood level of 10 metres is applied to all streams that have an upstream area above 1,312,479[57] grid cells (approximately 11,100 km^2). A square root curve was fitted between this point and the intersection of the x and y axes at a level of 0 metres and 0 cells of flow accumulation[58]. The resulting curve is defined by the function:

Flood Level = (0.0000762 * upstream area)$^{0.5}$

This gives the values for the upstream area for which different flood levels will be applied (Table 28).

Even in the biggest rivers the level is unlikely to exceed 10 m (above the mean flow) so smaller values should be also be considered. To account for this I will run a sensitivity analysis on the flood levels and on the flood buffers, and assess the differences in the flooded area per district.

[56] The values for a and b are based on the average values of a and b in Table 27
[57] The maximum flow accumulation in the dataset (in tile s05w080) is 13,124,790
[58] For large values of flow accumulation the curves fitted for river gauges give negative values for the level so a square root function was used instead to maintain positive values.

Table 28. Flood levels and buffers applied to streams based on upstream area

Upstream area (grid cells)	Maximum Flood Level	Flood Buffers around streams
1,312,479 – 13,124,790	10m	20km
328,120 – 1,312,479	5m	10km
209,997 – 328,120	4m	8km
118,123 – 209,997	3m	6km
52,499 – 118,123	2m	4km
13,124 – 52,499	1m	2km
1,000 – 13,124	0m	500m

I will run three different simulations (see Appendix 7) that alter the flood levels and buffers:

1. No limit on distance that flood water can flow, flood level determined by upstream area (Table 28). Maximum flood levels (for the largest rivers) are simulated for 2 m, 5 m and 10 m. There is very little data on observed maximum flood levels in Ecuador, so these levels are exploratory and based on reports of the impacts of the 1997-98 El Niño event (e.g. Instituto Nacional de Meteorología e Hidrología, 2005, pg16 and Dirección Nacional de Defensa Civil, 2002).
2. Distance that flood water can flow limited by buffer. Buffer distance is determined for each stream segment according to upstream area. Maximum buffers (for the largest rivers) are simulated for 20 km, 10 km and 5 km. Flood levels are the same for all streams. Flood levels are simulated for 2 m, 5 m and 10 m.
3. Both buffer and flood level determined by flow accumulation. Maximum buffers (for the largest rivers) are simulated for 20 km, 10 km and 5 km. Flood level is determined by flow accumulation. Maximum flood levels (for the largest rivers) are simulated for 2 m, 5 m and 10 m.

4.3.2 Landslide model

4.3.2.1 An ideal model and constraints to producing it

The ideal landslide model would be based on:

- a detailed inventory of past landslides
- for each landslide incident the relevant geotechnical information including topography, land-cover, soil and geology, and rainfall history
- potential triggers e.g. human-induced and seismic events (Basabe and Bonnard, 2002)

The model might be based on logistical regression or could use artificial neural networks to seek relationships between landslide occurrences and the co-variates mentioned above. A surface showing probabilities of landslide occurrence would then be produced.

As with the flood model there are three main constraints; data, software and hardware. In the case of the landslide model the lack of precise georeferenced data on landslide occurrence is the key constraint. As a result a model of landslide hazard risk for Ecuador will be limited to hypothetical links between landslides and data available at the national level.

Following Glade and Crozier (2005) I will therefore produce a series of models starting with a simple model similar to that proposed by Demoraes and D'Ercole (2001) based just on maximum slope gradient. I will then incorporate two other potential determinants of landslides: soil and a trigger factor corresponding to El Niño rainfall anomalies.

4.3.2.2 Landslide model for Ecuador based on slope only

Both Castellaños (2005) and Fabbri et al. (2003) have produced assessments of landslide susceptibility using topographic characteristics alone, among which maximum slope angles are the most important variable. Demoraes and D'Ercole (2001) use a slope angle of 12º to differentiate between areas at risk to landslides.

The actual gradient at which a slope fails will depend on many factors but if assumptions are made about the depth and type of material then slope stability models (e.g. Alcantara-Ayala, 2004) can provide insights into the effect of slope on the probability of failure.

The infinite slope model is used to provide a single number which is referred to as the Safety Factor. A value of 1 is the threshold between slope failure for values less than 1 and slope stability for values greater than 1.

$$SF = \frac{C + (\gamma - m\gamma_w) z \cos\beta \cos\beta \tan\phi}{\gamma z \sin\beta \cos\beta} \qquad (12)$$

Where C = cohesion (a property of the material measured in kN/m^2, values vary between 12 and 35 in the Alcantara-Ayala study.
γ is the unit weight of slope material measured in kN/m^3, values vary between 12 and 22 in the Alcantara-Ayala study.
γ_w is the unit weight of water measured in kN/m^3.
z is the thickness of slope material above the slide plane, values vary between 3 and 7 m in the Alcantara-Ayala study
z_w is the thickness of saturated slope material above the slide plane
m is the vertical height of the water table above the slide plane, expressed as a fraction of total thickness
β is the slope of the ground surface which is assumed parallel to the slope of the failure plane
φ is the internal angle of friction , values vary between 21 and 40 in the Alcantara-Ayala study.
(Alcantara-Ayala, 2004, pg37)

In the worse case where cohesion is absent, where the angle of internal friction is at the lower end of the normal range and where the whole layer above the slip plane is saturated the safety factor of 1 is breached just below a slope angle of 10°. Whereas for material with a cohesion value of $100kN/m^2$, and where the water table is only half way above the slip plane the safety factor value of 1 is never breached. Using average figures from Alcantara-Ayala (2004) the safety factor value of 1 is breached at a 40° slope.

This analysis suggests that landslides could occur on slopes as low as 10°, but would require saturation and the right type of material, while the conditions for landslides on slopes above 40° are far more likely and thus these areas are more susceptible. For this slope-only model I assume that slopes below 10° are not susceptible, while those above 30° are highly susceptible[59]. Weights are applied to slopes derived from the SRTM digital elevation model (Reuter et al., 2007) for the whole of Ecuador (Table 29). Not enough information is known to enable a more probabilistic derivation of weights but they are logical and are more nuanced than those applied by Demoraes and D'Ercole (2001).

Table 29. Weights applied to slope according to susceptibility

Slope	Susceptibility	Weight
0-10	Not susceptible	0
10-20	Low susceptibility	0.25
20-30	Moderate susceptibility	0.6
Above 30	High susceptibility	1

4.3.2.3 Landslide model for Ecuador based on slope and soil

This model is a multiplicative index of soil properties. Following Hong et al. (2007) and Lee and Choi (2004) I shall give greater weight to soils that are relatively thicker, coarser and well drained. The weighted soil map will then be combined with slope (using the model in section 4.3.2.2). The soil will have a moderating effect on the slope such that a shallow, impervious soil will reduce the effect of the slope by 0.5, while a well drained, deep and loose soil will have no effect on the slope. I shall use the soil map of Ecuador (Alianza Jatun Sacha – CDC Ecuador, 2003) to provide weights (Table 30). The categories in Table 30 are consistent with the soil map of Ecuador but the values are exploratory since Hong et al. do not publish the value of the weights used in their global landslide model.

It can be seen that a shallow, poorly drained, clay soil will have a weight of 0.8*0.8*0.8 = 0.51.

[59] 30° rather than 40° was chosen so that slopes close to, but slightly lower than 40° would be included in this class

Table 30. Weights applied to texture, depth and drainage of the soils of Ecuador

Map code	Description	Weight
Texture group		
1	Coarse sandy	1
2	Moderately coarse	0.95
3	Medium	0.9
4	Fine	0.85
5	Very fine	0.8
Depth		
1	0 – 20 cm	0.8
2	20 – 50 cm	0.86
3	50 – 100 cm	0.94
4	> 100 cm	1
Drainage		
1	Excessive	1
2	Good	0.94
3	Moderate	0.86
4	Poor drainage	0.8

4.3.2.4 Landslide model for Ecuador based on slope, soil and precipitation anomalies

This model is a simple extension of the model described in section 4.3.2.3. Those districts which experienced large precipitation anomalies experienced during the 1997-98 El Niño phenomenon in excess of 100% have been identified (section 3.2.2.2). Areas affected are given a value of 1 while those less affected a value of 0.5.

The rainfall anomaly index is then multiplied by the combined slope and soil index described in section 4.3.2.3. The resulting model gives values between 0 and 1 where the highest values are for slopes above 30° with deep, well-drained, coarse soils in districts that experienced large positive rainfall anomalies during the 1997-98 El Niño event.

4.3.3 District-level assessment of landslide and flood exposure potential

The flooding and landslide exposure models described above will be used in combination with socio-economic data to assess the vulnerability of districts, allowing for the better targeting of resources for disaster mitigation and preparedness. The exposure value for each district can be expressed as a percentage of the area of the district affected. This is easy to calculate and is especially suitable for evaluating the potential impact of floods and landslides on natural capital assets such as agricultural land. Alternatively the exposure could be calculated as a percentage of the population affected. This approach is more suitable for assessing the potential exposure of human and physical capital but relies on the availability of accurate and spatially explicit population data.

Data on population density have been modelled for Ecuador based on the location and size of settlements and interpolated in between (EcoCiencia, 2002). This method assumes that areas between settlements are more highly densely populated closer to known settlements than areas further away. District or census sector population figures were not used to modify these surfaces.

Other global population density surfaces e.g. Gridded Population map of the World (GPW) maintain district level total population values but do not distribute the population according to the location of settlements[60]. An important modification to the GPW is the Global Rural Urban Mapping Project (GRUMP) which has sought to better distribute population into rural and urban areas (Balk et al., 2004). This dataset benefits from the same fine-level population data used in GPW and also uses night-light imagery to define the extent of urban areas. During processing a routine is employed to distribute the population of each administrative unit while maintaining national thresholds of urban and rural population densities.

An alternative global source is the LandScan database of population products (ORNL, 1998). The LandScan products provide a dataset that takes advantage of a number of spatial data inputs to create a model of the distribution of population. These inputs are roads, slopes, land cover, populated places, coastlines, night light imagery, as well as exclusion areas and urban density factors (Dobson et al., 2000). The disadvantage of the LandScan dataset is the relatively coarse population data used, which in Ecuador is at the provincial rather than the district level (Balk et al., 2004).

Using the GPW dataset adds no value to the assessment of the population potentially exposed to floods and landslides so I will use both the GRUMP (for 1995) and the

[60] apart from the pixels at the boundary of the district which are modified depending on the density value in the neighbouring district

LandScan2006 datasets. GRUMP data are available for numerous dates and the same method is used to allocate the population, for this study there are data for 1995 and 2000. I shall use the data for 1995 to weight the exposure maps for the pre-El Niño situation. LandScan products are more difficult to compare due to changes in the methodology used, I therefore use the most up-to-date publicly available product for South America which is LandScan 2006.

These grids are used to calculate the total population in each district that is in the area liable to flood or experience landslides. These values are then compared to the total population and the proportion exposed to these hazards is calculated. Where weights are created, for instance in the landslide models, then the population will be multiplied by the weights and the proportion of the population affected per district is then calculated. In Figure 42 the sum of the population is 14,425, the weighted population sum is 772. The proportion of population affected is approximately 5%. The area affected, however, is 36% when the same weighting is applied to the area, without considering the population.

This will give a value that shows relative differences between districts, counties or provinces. The mean value is complemented by the sum of the weighted population potentially affected and is a useful indicator for the distribution of resources.

Weights

100	100	60	60
50	50	40	40
40	40	0	0
0	0	0	0

Population

0	25	200	200
20	50	40	1000
40	100	250	4000
0	500	3000	5000

Weighted Population

0	25	120	120
10	25	16	400
16	40	0	0
0	0	0	0

Figure 42. Weighting population using models of exposure

Due to the difference in resolutions between the flood and landslide models and the LandScan population data (in ESRI™ grid format) the flood and landslide results needed to be resampled to the coarser population data. The algorithms used in the resample tool within ArcGIS software are unsuitable for resampling from a 92 to 929 m cell size. The default resampling algorithm is the nearest neighbour method, but this only takes into account the 4 values closest to the centre of the larger cell. Even the more complex bilinear and cubic functions do not calculate the mean of all the smaller cells within the larger cell. To overcome this problem I needed to convert the model results to points, located at the centre of each raster cell. I then used a statistical function to calculate the mean value of the points within the larger cell size of the LandScan population grid. This has disadvantages in the long processing time but gives a more accurate result than the raster resampling algorithms (see Appendix 8).

4.4 Results

The results presented here are organised in three sub-sections. The first two sub-sections report on the area affected according to the flood and landslide models respectively. In each of these sub-sections the different flood and landslide simulations are contrasted, and are compared with the most precise existing assessments of floods or landslide hazards.

The third sub-section aggregates these results at the district level according to the area affected as well as the population, using two distinct population data sources. These results allow for the subsequent combination with socio-economic data in Chapter 5 to produce vulnerability assessments and approach the kind of information useful to policy analysts and national or regional planners.

4.4.1 Flood model

The simulations which capture the different assumptions of the effect of flow accumulation on flood levels and potential flood area produce very different results in terms of the flooded land area. The results of all 21 model runs can be summarised in terms of the area flooded for each region and for the whole country (Table 31). The differences between model runs are more or less consistent across regions although it could be argued that the effect of the buffer is most apparent in the Coast and Amazon regions where there are large areas of flat terrain situated next to large rivers.

Choosing a specific model is therefore problematic and the impact on hazard assessments and for the ranking of districts is potentially large. The results of each model run can be partially validated by a comparison with existing flood assessments (see section 4.1.2.1), although it has to be recognised that the model shows potential flood areas, which may differ with observed flood areas for any given rainfall event. Nevertheless these comparisons are useful for assessing the differences between simulations.

Table 31. Area flooded by region for each flood model simulation

	Area flooded by region (km^2)			
Flood Model	**Ecuador**	**Amazon**	**Andes**	**Coastal**
Flood level applied equally to all streams with no buffer				
10 m Flood no buffer	38,180	18,945	1,616	17,619
5 m Flood no buffer	21,346	9,040	674	11,633
2 m Flood no buffer	10,621	3,706	260	6,654
Flood level applied equally to all streams and buffer distance applied according to flow				
10 m flood and 20 km maximum buffer	30,966	14,660	1,531	14,775
10 m flood and 10 km maximum buffer	24,116	11,265	1,401	11,449
10 m flood and 5 km maximum buffer	15,608	7,402	1,141	7,064
5 m flood and 20 km maximum buffer	18,324	7,684	650	9,989
5 m flood and 10 km maximum buffer	15,116	6,343	597	8,175
5 m flood and 5 km maximum buffer	10,370	4,505	486	5,380
2 m flood and 20 km maximum buffer	9,336	3,390	252	5,695
2 m flood and 10 km maximum buffer	8,063	2,984	232	4,848
2 m flood and 5 km maximum buffer	5,906	2,287	188	3,431
Flood level and buffer distance applied according to flow accumulation				
10 m maximum flood and 20 km maximum buffer	9,609	2,917	215	6,477
10 m maximum flood and 10 km maximum buffer	8,055	2,681	200	5,174
10 m maximum flood and 5 km maximum buffer	5,990	2,250	171	3,569
5 m maximum flood and 20 km maximum buffer	6,393	1,414	94	4,886
5 m maximum flood and 10 km maximum buffer	5,468	1,366	90	4,012
5 m maximum flood and 5 km maximum buffer	4,229	1,299	86	2,844
2 m maximum flood and 20 km maximum buffer	3,713	450	22	3,242
2 m maximum flood and 10 km maximum buffer	3,220	446	22	2,753
2 m maximum flood and 5 km maximum buffer	2,486	437	21	2,027

Selecting an existing assessment of flood exposure to use as a validation dataset for Ecuador is difficult given that the accuracy of the sources is unknown. For a visual comparison between models over a small area I have selected the CAF-SENPLADES (2005) assessment, given that this study considers areas potentially susceptible to flooding. As mentioned in section 4.1.2.1 the CAF-SENPLADES data are available for very few areas and here I have selected a coastal upland area[61] in the county of Jipijapa in Manabí province to represent streams that have a maximum upstream area of approximately 200km^2.

[61] Elevation between 60 and 700m

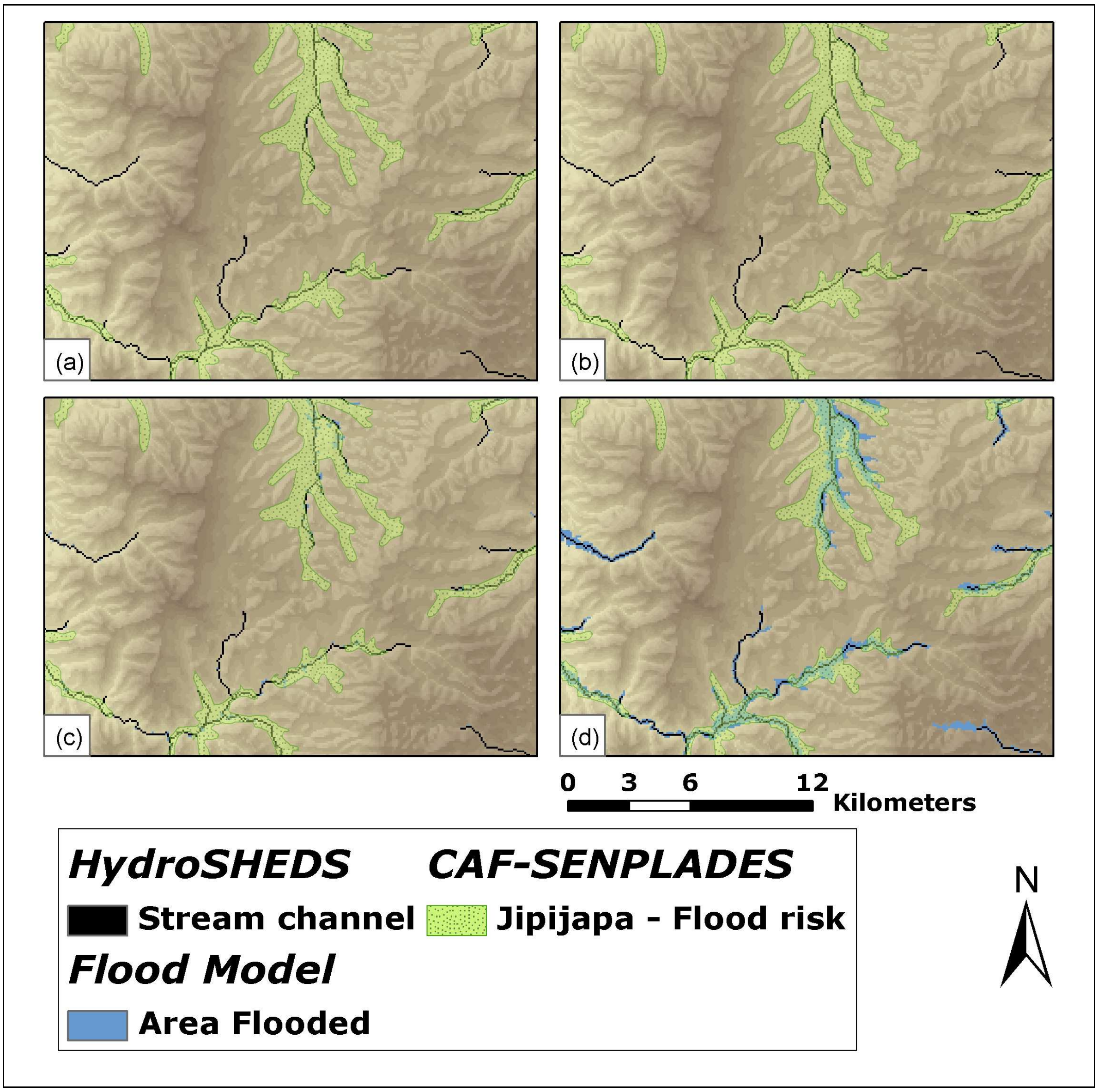


Figure 43. Comparison of flooded areas in upland catchments.

CAF-SENPLADES (2005) areas susceptible to flooding (a), and flooded area according to model for (b) 2 m maximum flood and 5km maximum buffer; (c) 2 m flood applied to all streams with no buffer, and; (d) 10 m flood applied to all streams with no buffer.

Figure 43 shows the CAF-SENPLADES flood assessment and the results of three flood models. The two flood models with the most restrictive assumptions (b and c) produce very few flooded areas in the selected location. However when a 10 m flood level is applied to all stream channels with no buffer the flooded area is considerably larger. It is clear that despite a high flood level there are some areas which are deemed susceptible to flooding by CAF-SENPLADES which are not flooded in the model. At the same time there are stretches of the stream which are flooded in the model but not in the CAF-SENPLADES assessment. Nevertheless for this upland coastal area it seems that the 10 m flood with no buffer is a better approximation of past assessments or observations than lower flood levels or when buffers are applied to limit the area flooded.

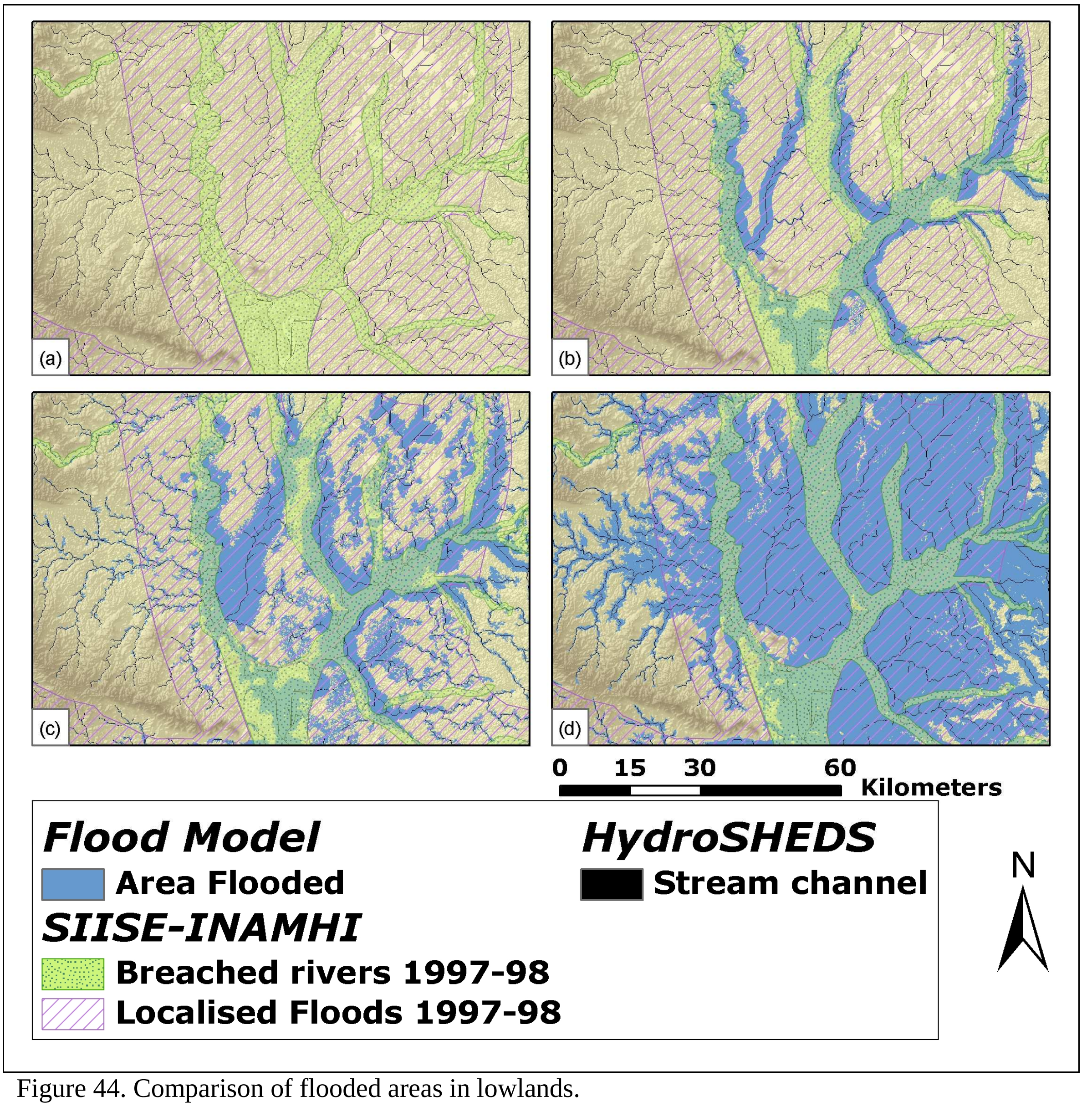


Figure 44. Comparison of flooded areas in lowlands.

Areas susceptible to flooding (a) and a range of model results for area flooded: (b) 2 m maximum flood and 5 km maximum buffer; (c) 2 m flood applied to all streams with no buffer, and; (d) 10 m flood applied to all streams with no buffer.

I now contrast these upland catchments with the lower Guayas basin in the south-centre of Ecuador, which is characterised by multiple stream channels where flooding has historically affected large areas of low-lying flat land. In this case the

flood simulations are compared to the rivers breached and localised flooding during the 1997-98 El Niño event (SIISE-INAMHI) because the CAF-SENPLADES source is not available for this area.
The size of the maximum distance of horizontal flow (the buffer) around each stream has a big impact on the flooded area (Figure 44). Even given the low precision and dubious accuracy[62] of the source it is clear that the simulation with a 10 m flood with no buffer (a) extends far outside the areas flooded due to the breach of rivers during the 1997-98 El Niño event, but is more or less within the same area affected by localised flooding. The best comparison with the SIISE-INAMHI flood map is the 2 m flood with no buffer (c). This captures the breaches of main channels as well as the localised flooding in the basin.

The differences between the flood simulation models based on HydroSHEDS and the SIISE-INAMHI maps of breached rivers and localised flooding combined can be analysed using a simple assessment of the percentage correspondence between the sources. Alternative methods of assessing the fit of the model are based on contingency tables that are constructed for each flood simulation model (e.g. Table 32). The tables show not only the degree of correspondence but also of disagreement which can be expressed quantitatively using statistical techniques more commonly used for comparing categorical maps such as landcover (e.g. Fritz and See, 2008), or ecological models (e.g. Couto, 2003). The Kappa coefficient was used originally in the rating of phenomena by two or more observers (Cohen, 1960) and ranges from a value of 1 which indicates perfect correspondence between the two sources being compared, to 0 which indicates a purely chance agreement between the two sources.

[62] When compared with both HydroSHEDS and the digital river network used in the Almanac Atlas of Ecuador

Table 32. Contingency table for a selected flood model simulation compared with SIISE-INAMHI dataset

		SIISE- INAMHI dataset of locally flooded areas and breached rivers in 1997-98 El Niño event		
		Number of cells flooded	Number of cells not flooded	Total
Model based on HydroSHEDS	Number of cells flooded	1,136,889	3,378,689	4,515,578
	Number of cells not flooded	1,081,252	23,409,989	24,491,241
	Total	2,218,141	26,788,678	29,006,819

kappa = 0.26 ; cellsize = 92m*92m

It can be seen that the highest correspondence in terms of the mutual agreement of the sources is for models that have small flood areas and low flood levels (Table 33), while the κ statistic is highest for a large flood maximum level and large maximum buffer. The absolute totals of both the percentage agreements and the values of the κ statistic suggest however that the agreement between the flood models and the maps of flooded areas is not large. This is in part due to the lack of precision in the map of observed flooding, especially those areas which suffered from local flooding but which are not flooded in any of the flood models (which assume a river breach). In general one would also make a preference for those models which overestimate the flooded areas since the flood model shows the impacts of a hypothetical flood which affects all areas equally, this was not the case in the El Niño event of 1997-98.

Table 33. Comparisons of area flooded for flood model simulations with SIISE- INAMHI dataset

	A	B	C	D	E	F	G
Flood level applied equally to all streams with no buffer							
10 m Flood no buffer	38,180	18,774	9,623	25	51	38	0.26
5 m Flood no buffer	21,346	18,774	7,026	33	37	35	0.29
2 m Flood no buffer	10,621	18,774	4,277	40	23	32	0.25
Flood level applied equally to all streams and buffer distance applied according to flow accumulation							
10 m flood and 20 km maximum buffer	30,966	18,774	8,386	27	45	36	0.27
10 m flood and 10 km maximum buffer	24,116	18,774	6,516	27	35	31	0.24
10 m flood and 5 km maximum buffer	15,608	18,774	4,020	26	21	24	0.18
5 m flood and 20 km maximum buffer	18,324	18,774	6,171	34	33	33	0.28
5 m flood and 10 km maximum buffer	15,116	18,774	5,066	34	27	30	0.25
5 m flood and 5 km maximum buffer	10,370	18,774	3,304	32	18	25	0.18
2 m flood and 20 km maximum buffer	9,336	18,774	3,769	40	20	30	0.23
2 m flood and 10 km maximum buffer	8,063	18,774	3,240	40	17	29	0.21
2 m flood and 5 km maximum buffer	5,906	18,774	2,302	39	12	26	0.16
Flood level and buffer distance applied according to flow accumulation							
10 m maximum flood and 20 km maximum buffer	9,609	18,774	4,877	51	26	38	0.31
10 m maximum flood and 10 km maximum buffer	8,055	18,774	3,855	48	21	34	0.25
10 m maximum flood and 5 km maximum buffer	5,990	18,774	2,618	44	14	29	0.18
5 m maximum flood and 20 km maximum buffer	6,393	18,774	3,798	62	20	41	0.28

5 m maximum flood and 10 km maximum buffer	5,468	18,774	3,121	60	17	38	0.23
5 m maximum flood and 5 km maximum buffer	4,229	18,774	2,171	54	12	33	0.17
2 m maximum flood and 20 km maximum buffer	3,713	18,774	2,532	72	13	43	0.21
2 m maximum flood and 10 km maximum buffer	3,220	18,774	2,202	73	12	42	0.18
2 m maximum flood and 5 km maximum buffer	2,486	18,774	1,633	71	9	40	0.14

A Area flooded in model based on HydroSHEDS (km^2)
B Area flooded in SIISE- INAMHI dataset (km^2)
C A∩B Area flooded in both based on HydroSHEDS and SIISE- INAMHI dataset (km^2)
D A∩B as % of area flooded in model based on HydroSHEDS
E A∩B as % of area flooded in SIISE- INAMHI dataset
F (D+E) / 2
G Agreement between Flood in Model and SIISE-INAMHI (κ)
Cells shaded yellow indicate models with greatest agreement

While no single simulation is able to exactly reproduce the areas flooded it is possible to choose a preferred model based on a visual and/or quantitative analysis – a 10 m maximum flood with a 20 km maximum buffer. The most restrictive models, i.e. those with a 2 m flood level and small buffers do not compare well with flood assessments in either the upland or lowland areas nor in the quantitative comparison. Without a precise source of observed flooding, however, the validation itself will not be convincing. The comparisons made in this section consider the areal extent of the flood models but do not take the population into account; this factor is considered in section 4.4.3.1.

The models developed in this chapter are likely to be an improvement on existing assessments given that higher resolution elevation models are now available, and users of such models would have access to the methodology used in their development. Besides the models can be easily be refined and re-validated as and when information is available on basin characteristics and stream channel morphologies, and on the spatial extents of actual events.

4.4.2 Landslide model

The result of the landslide model using solely the weights of the maximum slope is shown in Figure 45 (a). The darker areas signifying the steeper slopes are found principally on the flanks of the two ranges of the Andes mountain chain as well as a number of volcanoes in the inter-Andean valley. The coastal range of uplands is also noticeable.

When the model is compared to the slope map that was used in the assessment of Demoraes and D’Ercole (2001) it is clear that many coastal areas are omitted (Figure 45 [a]). There is a good correspondence, however, with the larger slope weights (60 and 100) in the landslide model. A visual comparison of the same data for a smaller area on the western flank of the Andes in central Ecuador reveals that there are still large differences between the maps, with many steep slope areas not identified in the Demoraes and D’Ercole map and vice versa (Figure 46). The reasons for these differences in unclear, given that the original elevation models produced by Souris (2001), compare well with the SRTM elevation model from which the slopes in the landslide model are derived.

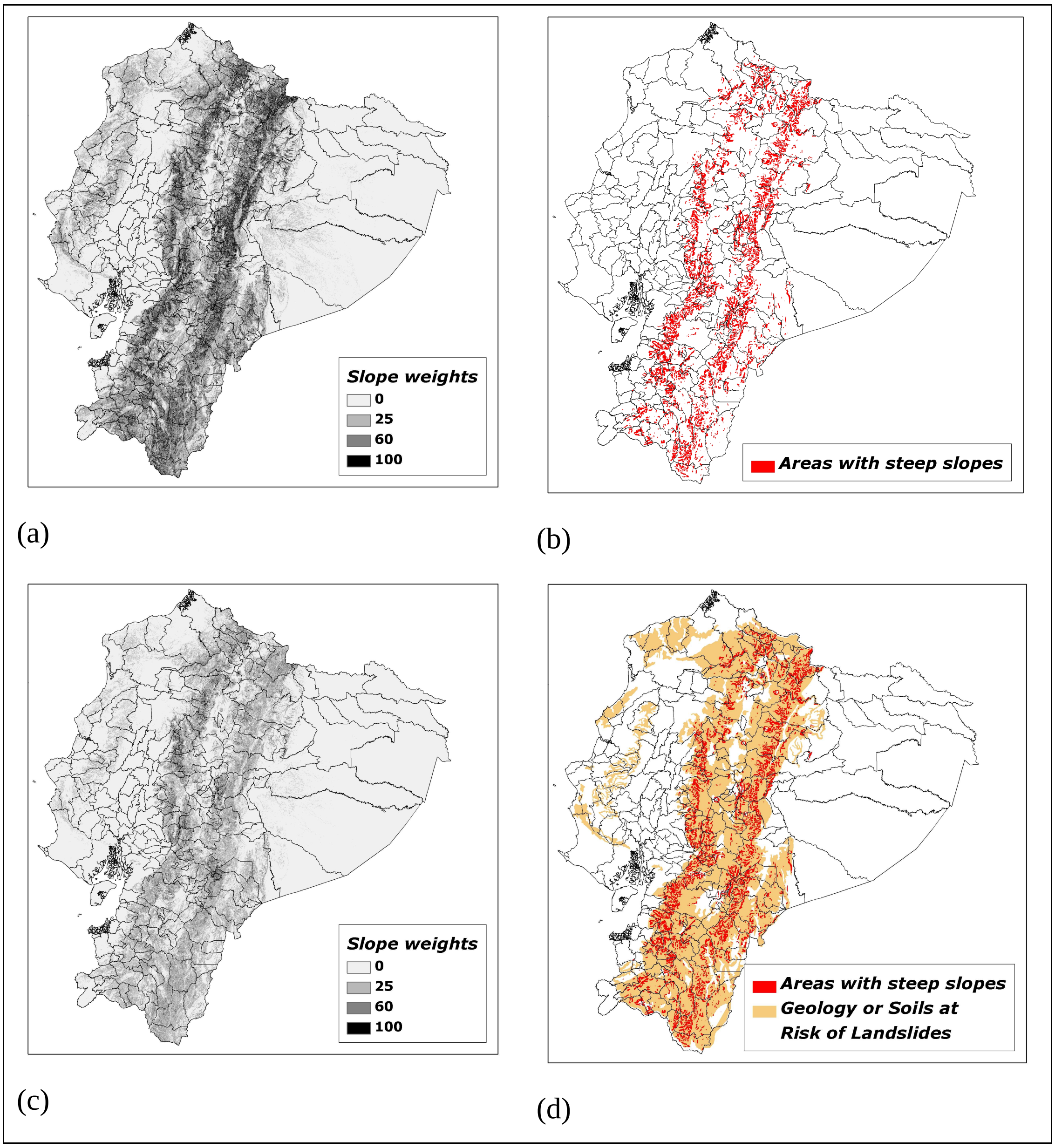


Figure 45. National comparison of landslide models with existing assessments.

(a) Landslide model using weighted slopes; (b) Demoraes and D'Ercole (2001) map of steep areas (>12º) (c) Landslide model using weighted slopes and soils; (d) Soils susceptible to Landslides and steep slopes (Demoraes and D'Ercole, 2001)

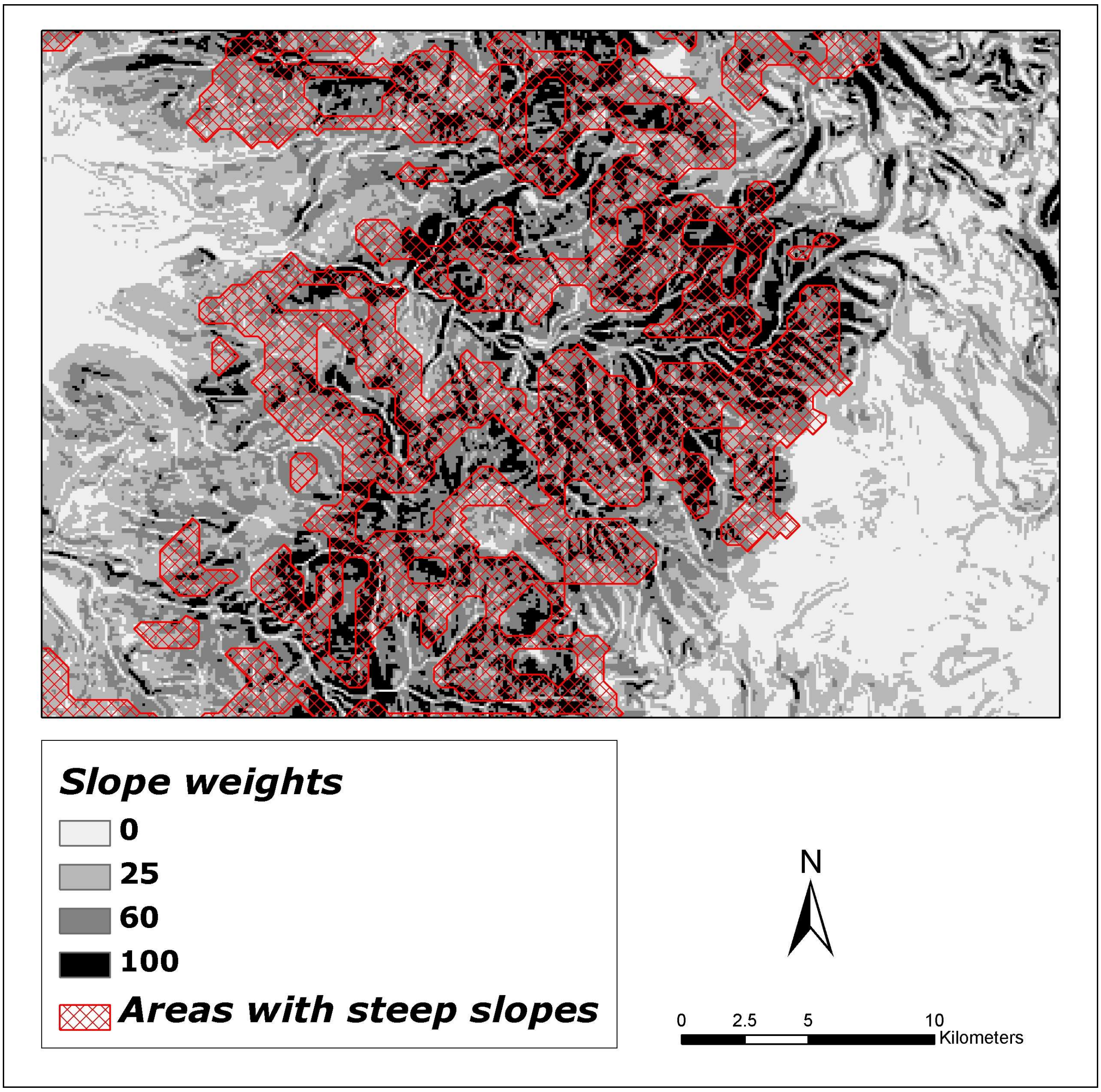


Figure 46. Comparison of landslide models with existing assessments in Azuay and Guayas provinces.

Landslide model using weighted slopes and Demoraes and D'Ercole (2001) map of steep areas (>12º)

Demoraes and D'Ercole combine slopes and soils (Figure 45[d]). This combination is explored in the subsequent variation of the model where susceptible soils are used to modify the slopes. Figure 47 shows the effect of soils on a small area of the coastal province of Manabí. The differences in Figure 47 between panels (a) and (c) are due to the modifying effect of the soils shown in panel (b), and in this particular area the steepest slopes generally don't coincide with the coarsest, deepest soils, consequently the weights of these slopes are reduced. Regarding the same model at the national scale (Figure 45[c]) it can be seen that the Andean region is still clearly the most susceptible to landslides.

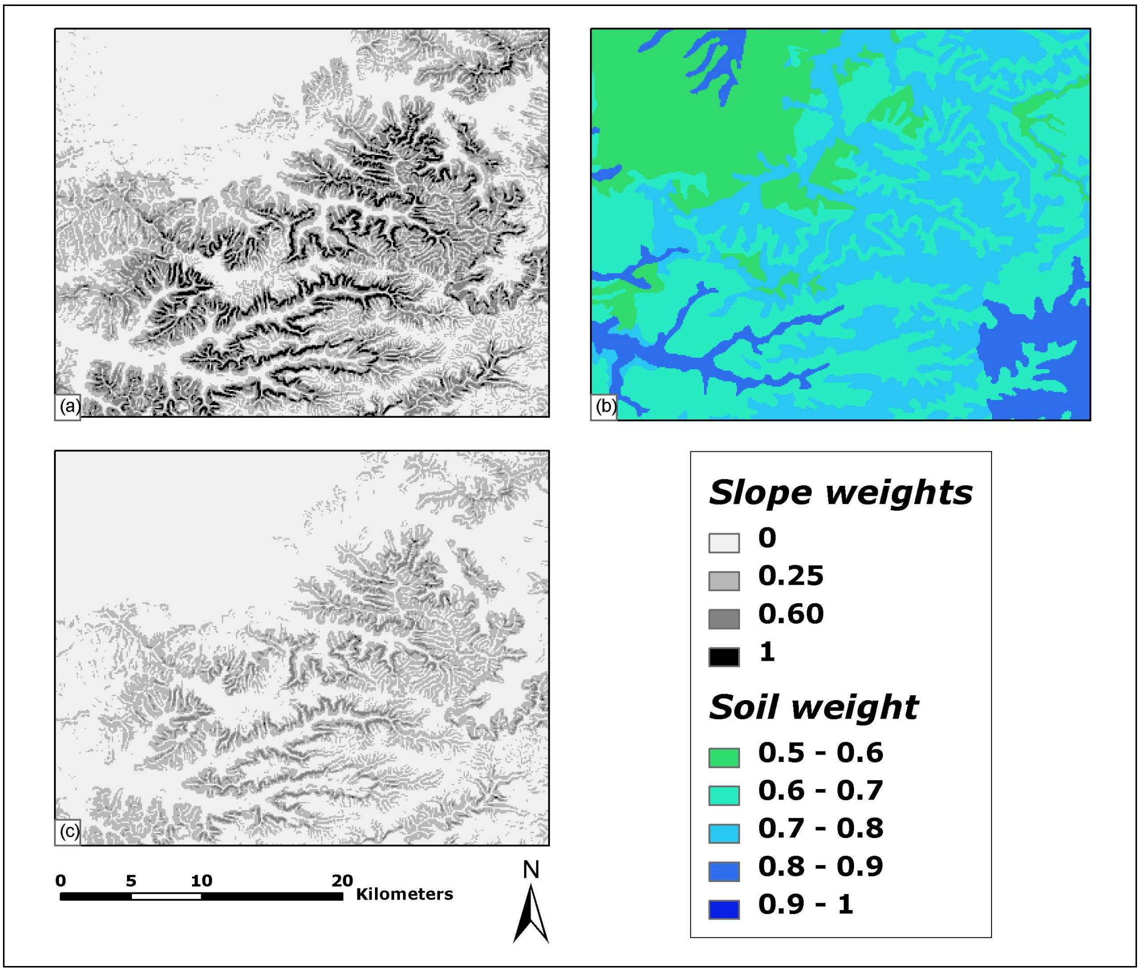


Figure 47. Combining slope and soil weights.

(a) Maximum slopes, weighted according to the likelihood of landslides; (b) soils weighted according to their susceptibility, and; (c) maximum slopes modified according to the soil weights and then re-weighted as in (a)

When the slopes are weighted according to those districts that experienced large positive rainfall anomalies the western fringe of the Andes cordillera is the region most affected (Figure 48) and the coastal uplands have similar values to the eastern flank of the Andes. There is no existing spatially explicit assessment with which to compare this model, instead the model needs to be summarised for each district or county and then compared to databases of actual events – this is explored in the following section.

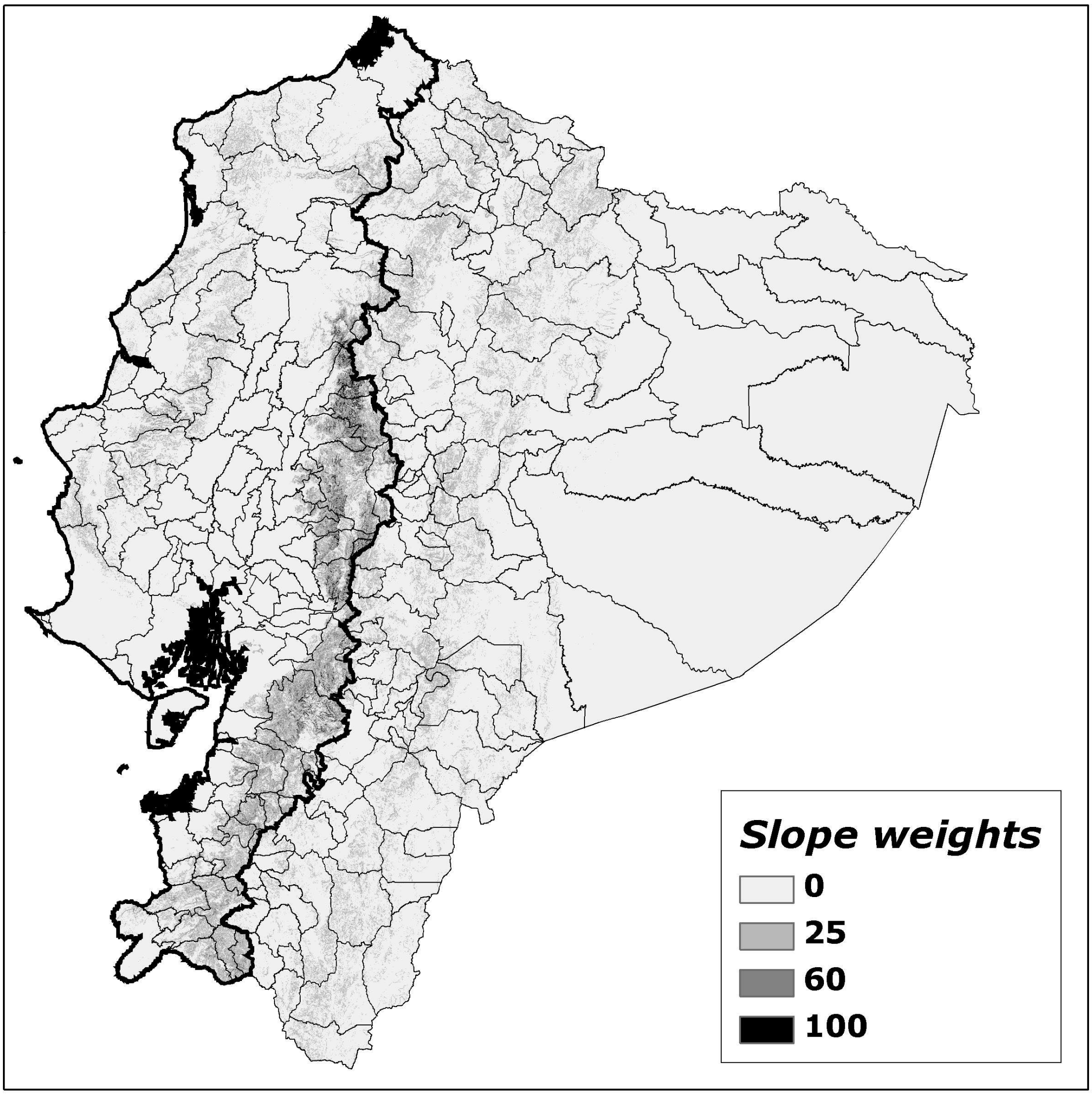


Figure 48. Landslide model using weighted slopes, soils and areas experiencing large rainfall amounts during El Niño events

4.4.3 District level assessment

4.4.3.1 District level assessments of flood models

The 21 distinct flood models have been compared to spatially explicit maps of previous flood events but these comparisons (Table 33) do not fully illustrate the differences between the models or with the SIISE-INAMHI assessment at the district level. District level summaries are important because it is at this level that the results can be linked with the household economic analysis and for informing the distribution of resources.

Table 34. Comparisons of ranks of districts flooded for flood model simulations with SIISE-INAMHI dataset.

Flood model	SIISE- INAMHI dataset of locally flooded areas and breached rivers in 1997-98 El Niño event	
	Total area flooded	Percentage of district flooded
Flood level applied equally to all streams with no buffer		
10 m Flood no buffer	0.476 (**)	0.503 (**)
5 m Flood no buffer	0.482 (**)	0.503 (**)
2 m Flood no buffer	0.473 (**)	0.488 (**)
Flood level applied equally to all streams and buffer distance applied according to flow accumulation		
10 m flood and 20 km maximum buffer	0.476 (**)	0.508 (**)
10 m flood and 10 km maximum buffer	0.471 (**)	0.507 (**)
10 m flood and 5 km maximum buffer	0.446 (**)	0.483 (**)
5 m flood and 20 km maximum buffer	0.483 (**)	0.507 (**)
5 m flood and 10 km maximum buffer	0.482 (**)	0.510 (**)
5 m flood and 5 km maximum buffer	0.469 (**)	0.503 (**)
2 m flood and 20 km maximum buffer	0.474 (**)	0.491 (**)
2 m flood and 10 km maximum buffer	0.474 (**)	0.496 (**)
2 m flood and 5 km maximum buffer	0.469 (**)	0.495 (**)
Flood level and buffer distance applied according to flow accumulation		
10 m maximum flood and 20 km maximum buffer	0.456 (**)	0.464 (**)
10 m maximum flood and 10 km maximum buffer	0.454 (**)	0.466 (**)
10 m maximum flood and 5 km maximum buffer	0.446 (**)	0.458 (**)
5 m maximum flood and 20 km maximum buffer	0.428 (**)	0.421 (**)
5 m maximum flood and 10 km maximum buffer	0.426 (**)	0.422 (**)
5 m maximum flood and 5 km maximum buffer	0.418 (**)	0.417 (**)
2 m maximum flood and 20 km maximum buffer	0.343 (**)	0.337 (**)
2 m maximum flood and 10 km maximum buffer	0.342 (**)	0.338 (**)
2 m maximum flood and 5 km maximum buffer	0.339 (**)	0.336 (**)

n = 989; Cells shaded yellow indicate models with greatest correlation coefficients; ** Correlation is significant at the 0.01 level (2-tailed). Spearman correlation coefficients of ranks of area per district liable to flood and the rank of districts flooded in the 1997-98 El Niño (INAMHI, 1999).

The flood models are summarised for each district according to two indicators: (i) the area flooded per district, and; (ii) the proportion of the district land area which is flooded. The ranks of each district are then calculated for each indicator and compared to the SIISE-INAMHI assessment.

The differences between the ranks of the area flooded per district from the preferred flood model from section 4.4.1 (a 10 m maximum flood with a 20 km maximum buffer), and the SIISE-INAMHI assessment are greatest in the Amazon region. This region was not affected during the 1997-98 El Niño event but experiences large areas flooded in the flood model. The ranks of the percentage of the area per district flooded show a more similar pattern, with flooding in the Lower Guayas basin more evident but still many districts in the northern Amazon have a high rank in the flood model.

When the correlations between the flood models and the SIISE-INAMHI maps are analysed the differences in the coefficients are not great but show similar patterns to the spatially explicit comparisons. The weakest correlations are between the SIISE-INAMHI assessment and those models with little land flooded (Table 34), while the strongest correlations are with the 5 m flood with 20 km buffer (in the case of total area flooded) and with the 5 m flood with 10 km buffer (in the case of % area flooded).

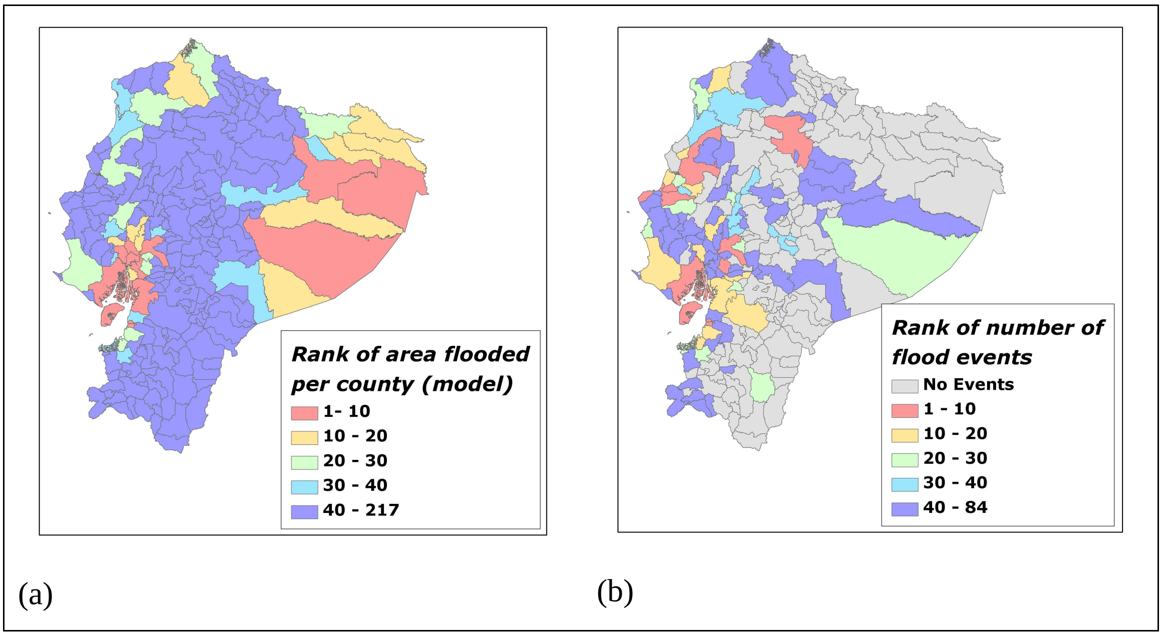


Figure 49. Comparisons of ranks of counties flooded for best fit flood model simulation with DesInventar dataset.
Ranks of counties according to (a) total area flooded with flood model of 10 maximum flood with a 20 km maximum buffer, and (b) total number of flood events reported (DesInventar, 2004)

This comparison is augmented by an analysis of the similarities and differences of the areas flooded when summarised at the county level in order to compare with the DesInventar (2004) database of recorded flood events shows an example of the comparison between the rank of counties according to the number of recorded events in DesInventar and the preferred flood model from section 4.4.1. Areas of both similarity and differences can be seen in these maps, and as with the comparison with the SIISE-INAMHI assessment the Amazon region has many highly ranked counties in the model, but has very few reported floods. Instead the DesInventar source gives higher ranks to more urban counties such as Guayaquil, Manta and Quito.

Table 35. Comparisons of ranks of counties flooded for flood model simulations with DesInventar dataset.

Flood model	Number of floods reported in DesInventar: Number of flood events	Number of floods reported in DesInventar: Rank of number of flood events
Flood level applied equally to all streams with no buffer		
10 m Flood no buffer	0.320 (**)	0.383 (**)
5 m Flood no buffer	0.440 (**)	0.412 (**)
2 m Flood no buffer	0.542 (**)	0.418 (**)
Flood level applied equally to all streams and buffer distance applied according to flow accumulation		
10 m flood and 20 km maximum buffer	0.270 (**)	0.388 (**)
10 m flood and 10 km maximum buffer	0.230 (*)	0.402 (**)
10 m flood and 5 km maximum buffer	0.177	0.401 (**)
5 m flood and 20 km maximum buffer	0.367 (**)	0.407 (**)
5 m flood and 10 km maximum buffer	0.321 (**)	0.415 (**)
5 m flood and 5 km maximum buffer	0.258 (*)	0.426 (**)
2 m flood and 20 km maximum buffer	0.468 (**)	0.414 (**)
2 m flood and 10 km maximum buffer	0.411 (**)	0.414 (**)
2 m flood and 5 km maximum buffer	0.343 (**)	0.422 (**)
Flood level and buffer distance applied according to flow accumulation		
10 m maximum flood and 20 km maximum buffer	0.406 (**)	0.375 (**)
10 m maximum flood and 10 km maximum buffer	0.373 (**)	0.374 (**)
10 m maximum flood and 5 km maximum buffer	0.332 (**)	0.387 (**)
5 m maximum flood and 20 km maximum buffer	0.430 (**)	0.401 (**)
5 m maximum flood and 10 km maximum buffer	0.396 (**)	0.399 (**)
5 m maximum flood and 5 km maximum buffer	0.367 (**)	0.401 (**)
2 m maximum flood and 20 km maximum buffer	0.531 (**)	0.380 (**)
2 m maximum flood and 10 km maximum buffer	0.473 (**)	0.378 (**)
2 m maximum flood and 5 km maximum buffer	0.418 (**)	0.370 (**)

n = 94; Cells shaded yellow indicate models with greatest correlation coefficients;** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed)

Pearson correlation coefficients of area per county liable to flood and the number of floods reported in DesInventar, and Spearman correlation coefficients of ranks of area per county liable to flood and the number of floods reported in DesInventar.

When the correlations are calculated with all of the flood models (Table 35) the total number of flood events in the DesInventar database is most strongly correlated with the flood model with a 2 m maximum flood level with no buffer. However when the counties are ranked in order of the greatest number of floods and the rank of the area per county flooded in the model the strongest correlation is with a flood model of a 5 m flood with a 5 km maximum buffer (Table 35).

The preceding comparison looks solely at the area affected per county, and the impact in counties in the Amazon with large areas but small populations is perhaps overestimated. A better comparison with the DesInventar database of reported flood events can be made if the population potentially exposed to flooding is summarised for each county in Ecuador according to the different models developed.

Table 36. Comparisons of ranks of counties according to population affected using the LandScan2006 database for flood model simulations with DesInventar dataset.

	Rank of number of deaths	Rank of number of people affected
Flood level applied equally to all streams with no buffer		
10 m Flood no buffer	0.437(**)	0.501(**)
5 m Flood no buffer	0.428(**)	0.503(**)
2 m Flood no buffer	0.409(**)	0.494(**)
Flood level applied equally to all streams and buffer distance applied according to flow accumulation		
10 m flood and 20 km maximum buffer	0.439(**)	0.549(**)
10 m flood and 10 km maximum buffer	0.457(**)	0.576(**)
10 m flood and 5 km maximum buffer	0.460(**)	0.558(**)
5 m flood and 20 km maximum buffer	0.436(**)	0.536(**)
5 m flood and 10 km maximum buffer	0.437(**)	0.575(**)
5 m flood and 5 km maximum buffer	0.458(**)	0.573(**)
2 m flood and 20 km maximum buffer	0.410(**)	0.525(**)
2 m flood and 10 km maximum buffer	0.419(**)	0.553(**)
2 m flood and 5 km maximum buffer	0.426(**)	0.550(**)
Flood level and buffer distance applied according to flow accumulation		
10 m maximum flood and 20km maximum buffer	0.388(**)	0.454(**)
10 m maximum flood and 10 km maximum buffer	0.392(**)	0.470(**)
10 m maximum flood and 5 km maximum buffer	0.393(**)	0.471(**)
5 m maximum flood and 20 km maximum buffer	0.386(**)	0.430(**)
5 m maximum flood and 10 km maximum buffer	0.390(**)	0.446(**)
5 m maximum flood and 5 km maximum buffer	0.394(**)	0.451(**)
2 m maximum flood and 20 km maximum buffer	0.255(*)	0.312(**)
2 m maximum flood and 10 km maximum buffer	0.253(*)	0.322(**)
2 m maximum flood and 5 km maximum buffer	0.253(*)	0.334(**)

n = 94; Cells shaded yellow indicate models with greatest agreement; ** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed) Correlation coefficients (Spearman) of ranks of population per county affected by flood models using the LandScan2006 database, and the number of deaths and number of people affected by all floods in the DesInventar database

The sum of the population is calculated for each flood model for each county and the counties are ranked in order of the highest population in the flood areas. The counties are also ranked according to the number of floods, the number of deaths and the number of people affected as reported in the DesInventar database. Correlations between these ranks are then calculated and can be seen in , which uses the LandScan 2006 population database, and Table 37, which uses the GRUMP population database.

Table 37. Comparisons of ranks of counties according to population affected using the GRUMP database for flood model simulations with DesInventar dataset.

	Rank of number of deaths	Rank of number of people affected
Flood level applied equally to all streams with no buffer		
10 m Flood no buffer	0.358(**)	0.372(**)
5 m Flood no buffer	0.357(**)	0.357(**)
2 m Flood no buffer	0.359(**)	0.343(**)
Flood level applied equally to all streams and buffer distance applied according to flow accumulation		
10 m flood and 20 km maximum buffer	0.365(**)	0.398(**)
10 m flood and 10 km maximum buffer	0.360(**)	0.410(**)
10 m flood and 5 km maximum buffer	0.370(**)	0.409(**)
5 m flood and 20 km maximum buffer	0.356(**)	0.382(**)
5 m flood and 10 km maximum buffer	0.353(**)	0.406(**)
5 m flood and 5 km maximum buffer	0.359(**)	0.400(**)
2 m flood and 20 km maximum buffer	0.354(**)	0.358(**)
2 m flood and 10 km maximum buffer	0.353(**)	0.372(**)
2 m flood and 5 km maximum buffer	0.353(**)	0.384(**)
Flood level and buffer distance applied according to flow accumulation		
10 m maximum flood and 20 km maximum buffer	0.329(**)	0.327(**)
10 m maximum flood and 10 km maximum buffer	0.329(**)	0.333(**)
10 m maximum flood and 5 km maximum buffer	0.328(**)	0.348(**)
5 m maximum flood and 20 km maximum buffer	0.334(**)	0.317(**)
5 m maximum flood and 10 km maximum buffer	0.336(**)	0.327(**)
5 m maximum flood and 5 km maximum buffer	0.336(**)	0.339(**)
2 m maximum flood and 20 km maximum buffer	0.224(*)	0.272(**)
2 m maximum flood and 10 km maximum buffer	0.226(*)	0.276(**)
2 m maximum flood and 5 km maximum buffer	0.230(*)	0.280(**)

n = 94; Cells shaded yellow indicate models with greatest agreement; ** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed) Correlation coefficients (Pearson) of ranks of population per county affected by flood models using the GRUMP database, and the number of deaths and number of people affected by all floods in the DesInventar database

The tables show that all the coefficients are significant at the 95% level, with the majority significant at the 99% level. Another observation is that the correlation coefficients are universally higher when the Landscan2006 population database is used to assess the population in the areas flooded and when the ranks of the number of people affected are used rather than the number of deaths. These are probably due in the first case to the better spatial resolution of the population in the Landscan2006 product, and in the second case because of the relatively small number of deaths due to flooding.

Differences between the coefficients are not large except for the flood models that have the smallest areas (i.e. 2 m maximum flood levels with buffers). These models only affect a relatively small proportion of counties in the Lower Guayas basin, where apart from in the city of Guayaquil the number of deaths or affected people was smaller than in other counties that are not significantly flooded in these models.

The flood model with the highest correlation to the number of people affected is a 10 m flood with a 10 km maximum buffer (highlighted in yellow in the table). For this model two maps are displayed, firstly the absolute number of people in the areas potentially flooded, and secondly the percentage of the population potentially exposed (Figure 50). The results were calculated for each district but are displayed at the county level so that visual comparisons can be made more easily. Districts and counties with the greatest population potentially exposed to flooding are generally those found in the Guayas basin north of the city of Guayaquil, (Figure 50 [a]) but also include the major cities of Quito, and Cuenca in the Andean region and Esmeraldas in the northern coastal region. The map of the percentage of the population affected (Figure 50 [b]), shows a slightly different pattern and the cities in the Andean region decrease in importance.

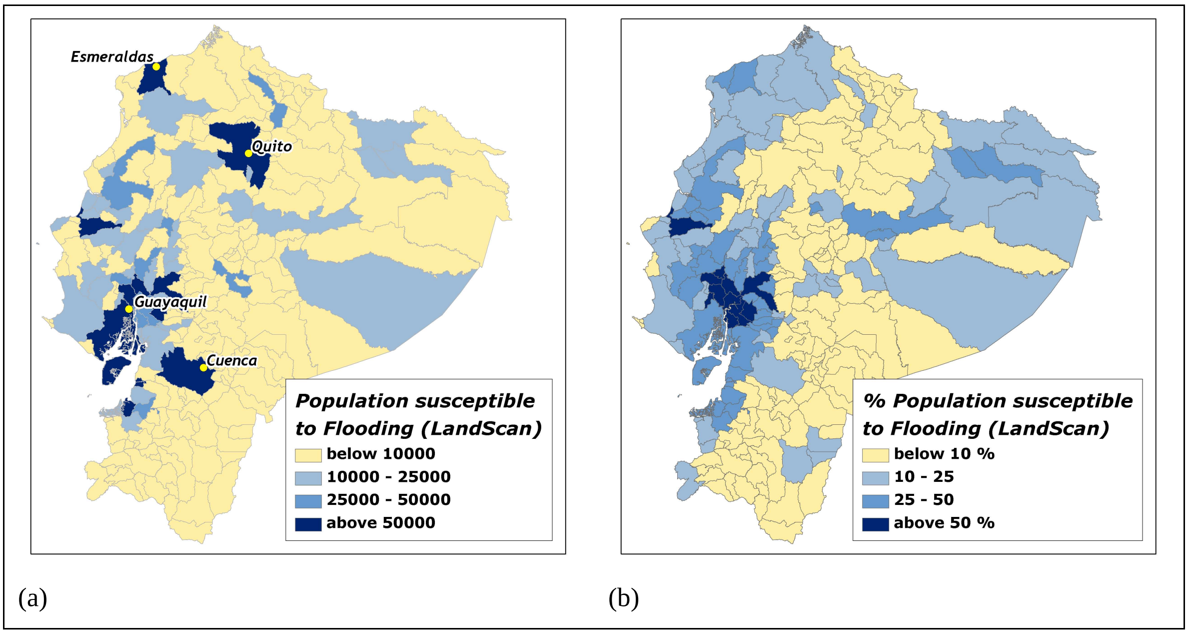


Figure 50. (a) Total population per county, and; (b) Percentage of population per county potentially exposed to flooding with a 10 m flood and 10 km maximum buffer

The differences between the proportion of the population affected and the total amount per district or county suggest that both indicators could be used in an assessment of potential exposure to flooding. As with maps of poverty incidence vs. density (e.g. Minot and Baulch, 2005) the choice depends on the kind of intervention required and the relationship between the costs and benefits.

4.4.3.2 District level assessments of landslide models

As with the flood models the areas susceptible to landslides were calculated for each district but are displayed at the county level so that visual comparisons can be made with summaries of previous assessments (Figure 33) and, importantly, with the actual numbers of reported landslides (Figure 34).

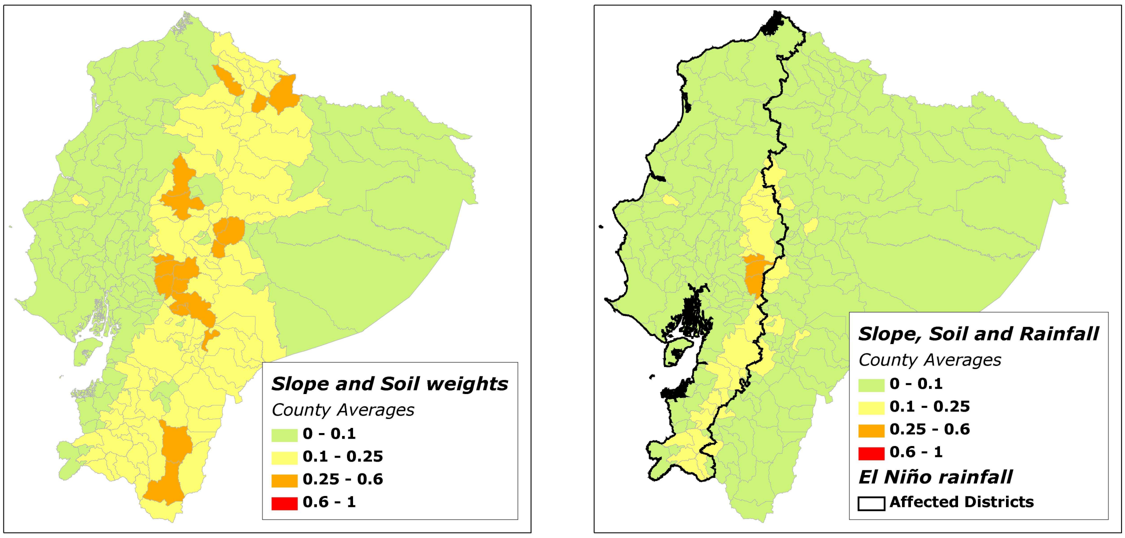
The first model which considers just slopes is highly correlated with existing landslide assessments that use similar methods and data. However the same model bears little relationship with the location of landslides recorded in the DesInventar (2004) database. Similarly the Spearman coefficient measuring the correlation of the ranks of counties for the ‘slope only’ landslide model against the number of landslides is very close to zero (Table 38).

Table 38. Comparisons of ranks of counties susceptible to landslides
Correlation coefficients (Spearman) of ranks of area per county susceptible to landslides, the rank of counties with large areas of 'steep slopes' (Demoraes and D'Ercole, 2001), and the rank of the number of landslides reported per county in the DesInventar database

	Rank of area of steep slope (Demoraes)	Rank of number of landslides
Slopes	0.881 (**)	0.213 (*)
Slopes and Soils	0.891 (**)	0.149
Slopes and Soils and Rainfall	0.735 (**)	0.287 (**)

* Correlation is significant at the 0.05 level (2-tailed); ** Correlation is significant at the 0.01 level (2-tailed).

Possible reasons for this lack of correlation are that the soils in the Andean region which have the largest areas of steep slopes are less susceptible to landslides, or that there are insufficient triggers in the Andean region to cause many landslides. The correlation between the models that incorporate soils (Figure 51(a)) and precipitation anomalies (Figure 51(b)) are also very low, however (Table 38).



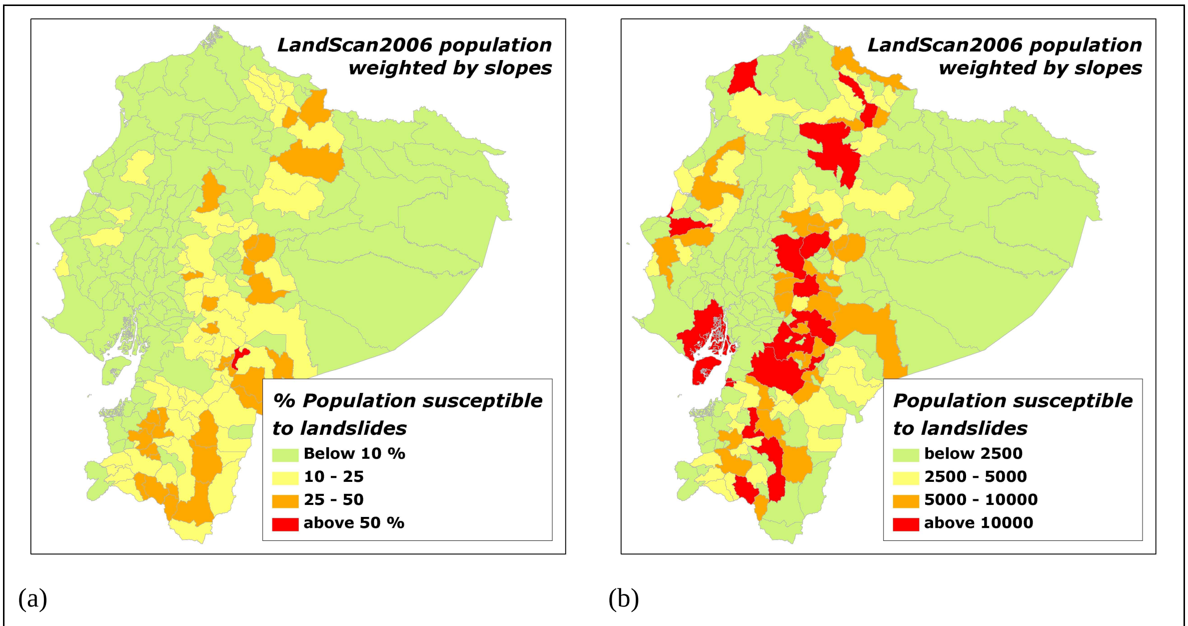
(a) (b)

Figure 51. (a) Counties weighted by slopes and soils, and (b) Counties weighted by slopes, soils and districts affected by large positive rainfall anomalies during the 1997-98 El Niño event

Those counties in the coastal region that had large incidents of landslides are not apparent in the maps of any of these models of landslide hazards, nor in previous assessments. One possible reason is that the reporting of landslides is only likely if there are impacts on the population, which would imply that landslides occurring in more densely populated areas would show a higher correlation with those reported in the DesInventar database than landslides in sparsely populated zones. This prospect is now considered.

The first landslide model uses only slopes to weight the population potentially exposed to landslides. The higher the slope the more susceptible the location and the greater the weight applied to the spatially disaggregated population surface. The percentage of the population affected in each county is shown in (Figure 52 [a]). Differences can be seen when compared to the area susceptible using the same model (Figure 45[a]), most notably in the northern Andes and Coastal regions. These are areas where steep slopes are often encountered in remote forest areas with little human habitation. In contrast the slopes of the eastern cordillera of the Andes, especially in the south of the country, are where the highest proportions of populations potentially exposed are estimated.

An alternative means of displaying the susceptible population is to map the total population within each county (Figure 52 [b]). This map highlights those counties which have a large population but this kind of result shows where most people will be affected. The map is also a better comparison with the database of reported landslide incidents although the pattern still shows differences especially in the central Andean and coastal regions.



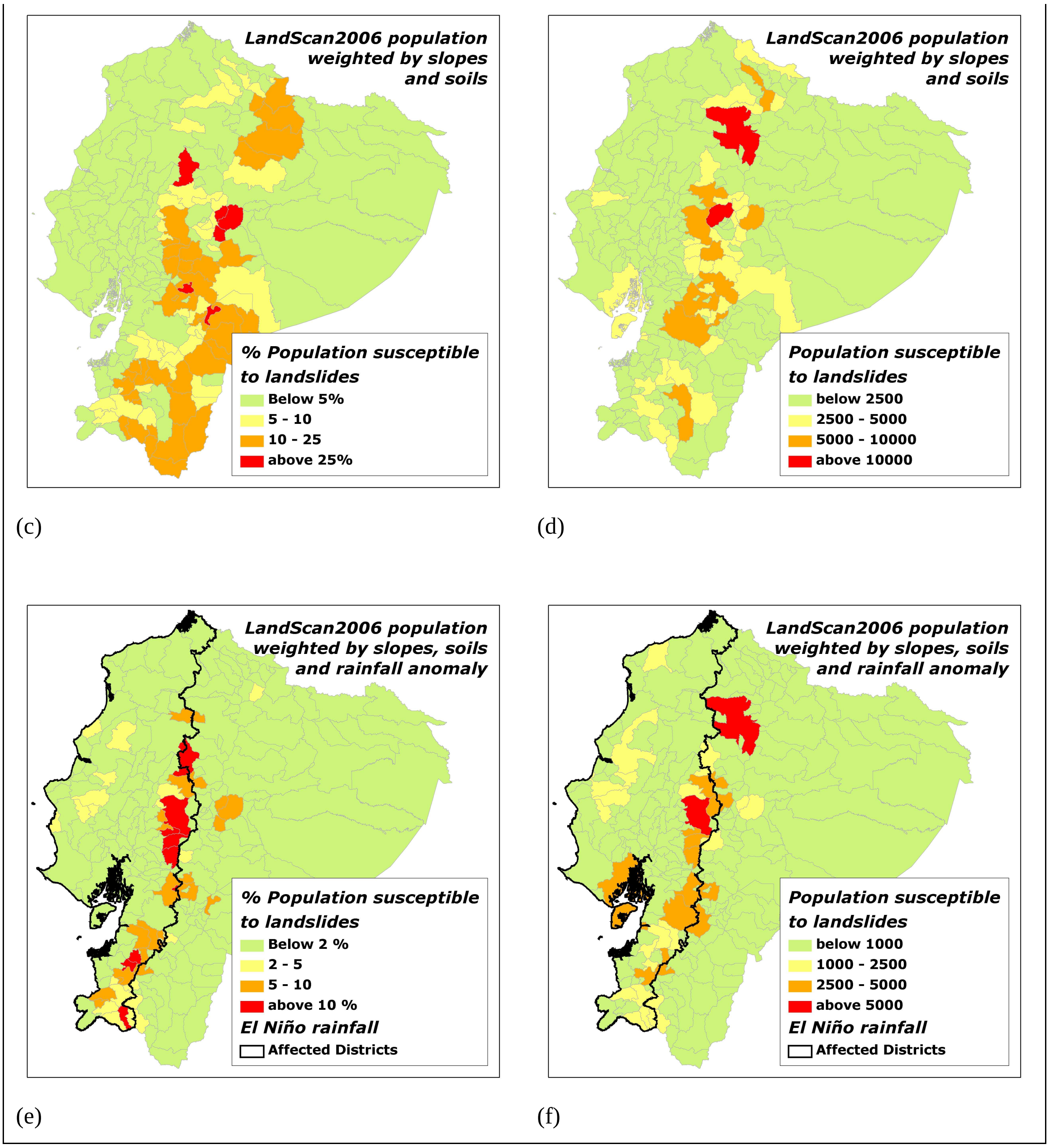
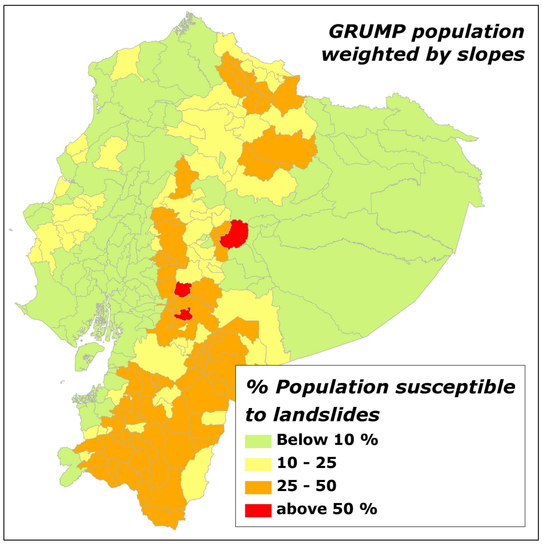


Figure 52. Comparisons of population per county susceptible to landslides using LandScan2006 database.

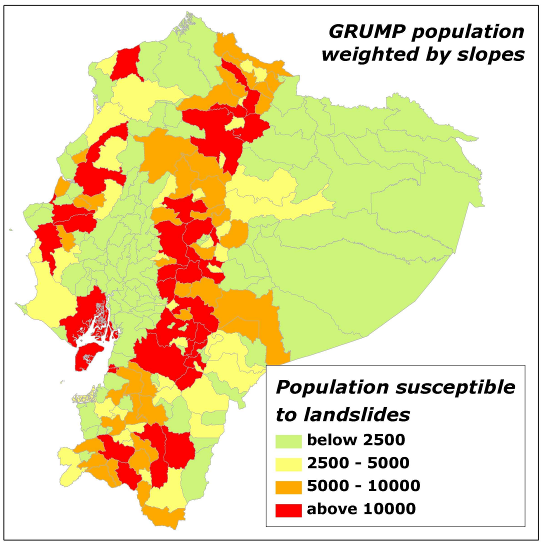
(a) Percentage of population per county, and (b) Population per county susceptible to landslides weighted by slopes. (c) Percentage of population per county and (d) Population per county susceptible to landslides weighted by slopes and soils. (c) Percentage of population per county, and (d) total population per county weighted by slopes, soils and districts affected by large positive rainfall anomalies during the 1997-98 El Niño event using LandScan2006 data

When soils are incorporated into the landslide model the pattern of counties most affected does not alter considerably (Figure 52 [c] and [d]) and as with the model using just slopes the maps showing the total population potentially exposed better reflects the reports of landslide incidents.

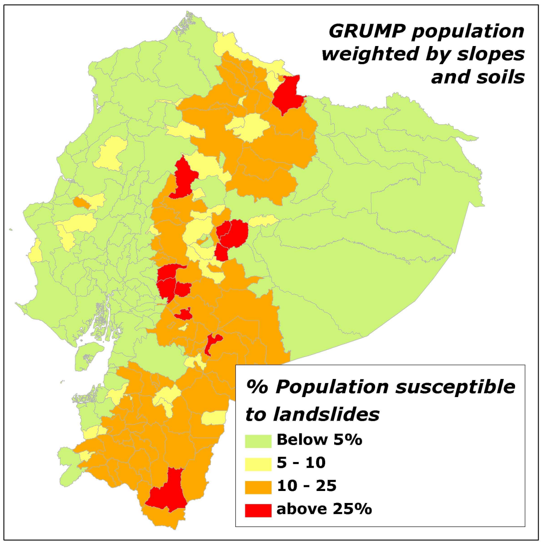
In the third landslide susceptibility model slopes are modified by soils and a variable for rainfall anomalies as observed during the 1997-98 El Niño event. Neither the percentage nor the total population susceptible to landslides are radically different to the areas deemed susceptible within each county (compare Figure 52 [e] and [f] with Figure 51 [b]).



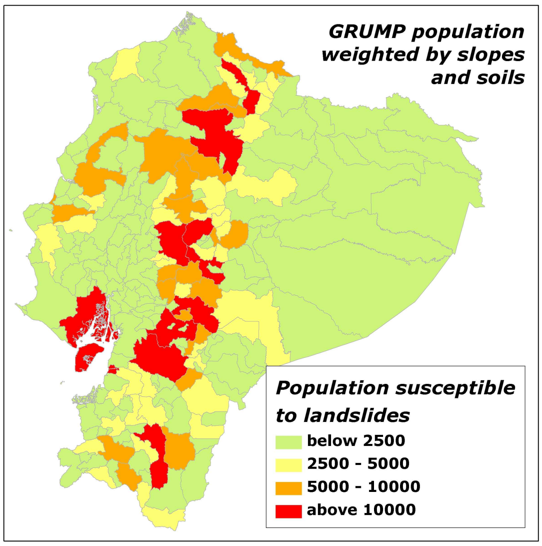
(a)



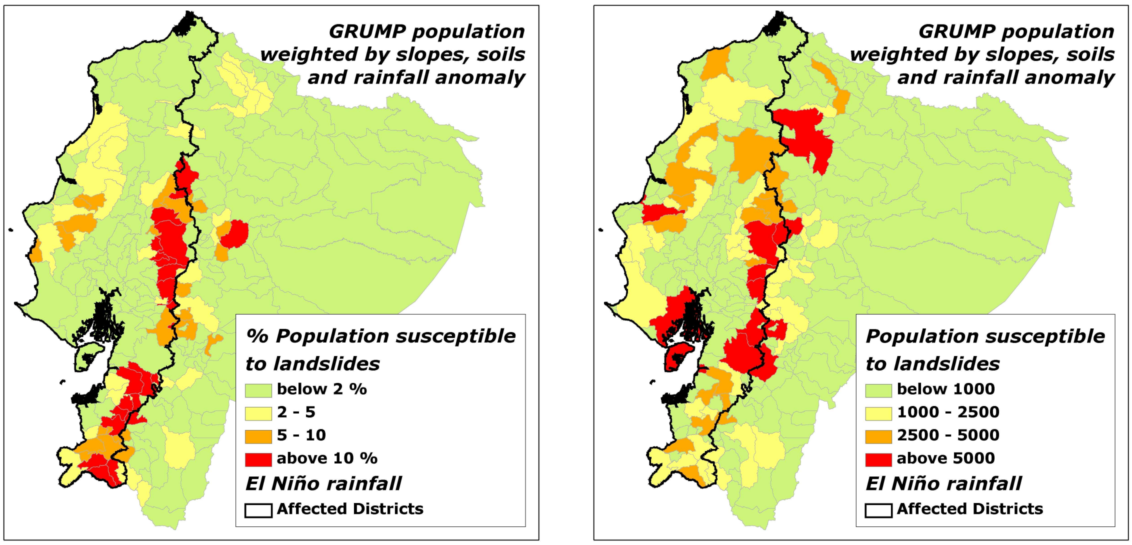
(b)



(c)



(d)



(e) (f)

Figure 53. Comparisons of population per county susceptible to landslides using GRUMP database.

(a) Percentage of population per county, and (b) Population per county susceptible to landslides weighted by slopes. (c) Percentage of population per county and (d) Population per county susceptible to landslides weighted by slopes and soils. (c) Percentage of population per county, and (d) total population per county weighted by slopes, soils and districts affected by large positive rainfall anomalies during the 1997-98 El Niño event using GRUMP population data

When the GRUMP population data are used to assess the potential impact of these events (Figure 53) there are some slight changes in the counties that appear worst affected, notably in the southern Andes and coastal region. In addition the total number and percentages of the population potentially affected by landslides are higher than when the LandScan2006 data source is used.

These differences can be further explored by examining the correlation between the ranks of the population per county deemed exposed to landslides, and the ranks of the reported number of people affected (Table 39). This shows that in contrast to the flood models the use of the GRUMP population database allows for a stronger correlation than using the LandScan2006 source of population data. This may be due to the fact that the population in GRUMP is higher in rural areas away from the urban centres; these also tend to be areas affected by landslides. Additionally it can be seen that the correlations are more significant than when the population is not considered (Table 38). The correlation between the ranks of the number of deaths is stronger than for the number of people affected, especially for the model that considers slopes and soils.

Table 39. Comparisons of ranks of counties according to population affected for landslide models with DesInventar dataset.

	Rank of number of deaths	Rank of number of people affected
Landslide models (with LandScan2006 population)		
Slopes	0.488(**)	0.220(*)
Slopes and Soils	0.452(**)	0.170
Slopes and Soils and Rainfall	0.390(**)	0.231(*)
Landslide models (with GRUMP population)		
Slopes	0.550(**)	0.283(**)
Slopes and Soils	0.500(**)	0.219(*)
Slopes and Soils and Rainfall	0.435(**)	0.296(**)

n = 97; ** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed)

Correlation coefficients (Spearman) of ranks of population per county affected by landslide models using the LandScan2006 and GRUMP databases, and the number of deaths and number of people affected by all landslides in the DesInventar database

The most significant correlation is found for the slopes only model, regardless of the population source used which to some extent supports Glade and Crozier's (2005) and Fabbri et al.'s (2003) view that simple models (with in this case fewer assumptions) are often more powerful predictors of the impacts of landslides.

4.5 Discussion of findings

This chapter has reviewed assessments of floods and landslides in Ecuador. Ideal flood and landslide models have been proposed and the constraints have been identified. Models for both floods and landslides have been developed according to the data, software and hardware available. The areas, populations and districts potentially exposed to these hazards have been highlighted. Each model incorporates assumptions and the sensitivity of the results to these assumptions and the data has been tested. There are a number of issues which this chapter highlights and which warrant further discussion. These issues include recommendations about minimum data requirements, the need for flexibility in choosing models for a given purpose, and the need for improved methods for validating the flood and landslide models. This section will conclude with recommendations for further research.

The models developed in this chapter seek to analyse the feasibility of increasing the complexity of national level modelling based on the availability of higher resolution elevation and hydrological datasets, in accordance with the conceptual framework proposed by Glade and Crozier (2005). They have shown not only that it is feasible to produce models but that these models are more highly correlated than previous assessments to actual incidents of floods and landslides. Summaries of the hazard models at the district level move the results of the models along the technical-political continuum and allow the incorporation of other socio-economic data and an analysis of the sensitivity of the models in terms of the recommendations for resource allocation. The analysis shows that the flood models are generally robust to all but the greatest changes in the assumptions. In addition the comparison with existing records of impacts allows for the selection of a preferred model even though the comparisons with the DesInventar source are far from perfect.

Ideal models have been described for areas susceptible to landslides and potentially exposed to flood hazards. It has been shown, however, that there are serious constraints in developing these ideal models. An issue with all of the models developed in this chapter is that they are based on other models. The principal dataset used in the flood models for Ecuador is HydroSHEDS. It has been shown that there are differences between the stream channels used in the creation of the dataset and those that appear in national atlases and which satellite imagery confirm are in the correct location. The results of these errors are encountered not just in the location of streams (which flood) but also in the flow accumulation. These errors will affect not just the location of modelled flood events but also the magnitude of those events. A concerted effort is required therefore to improve the HydroSHEDS dataset, based on data which might not have been available to the team that developed the data. In addition the ‘burning’ of the stream channels into the HydroSHEDS data has created artificial buffers around streams which could have a direct impact on the kind of flood modelling developed in this chapter.

The differences in the landslide models are due to assumptions about the susceptibility of soils to mass movements. These assumptions are based on global studies rather than on recommendations for Ecuador. A change in the assumptions – for instance, that soils with greater clay content are more prone to landslides – or to the weights given, or even to the quality of the data will have a potentially significant impact on the areas that are susceptible. The development of landslide models based on an empirical relationship between incidents and possible determinants is hampered in Ecuador by potential bias and lack of precision in the reporting of incidents. A national scale inventory of landslide events is therefore required to improve the determination of the weights.

The incorporation of population estimates for areas susceptible to landslides or potentially exposed to flooding are also an innovation for national scale assessments in Ecuador. The population data used to assess the impact of the flood and landslide models are themselves models which are based on a number of other sources. When the best-fit flood model was selected the combination of a 10 m flood and 10 km maximum buffer and the LandScan2006 population data showed a slightly stronger correlation to the DesInventar database. In contrast the alternative population source, GRUMP, gave higher correlations in the case of the landslide models. The differences between these two global models of the distribution of the population are not great but the results underline the importance of further improvements in the spatial resolution of population datasets.

Much of the economic loss associated with the 1997-98 El Niño event was due to impacts on agricultural production and damage to buildings and infrastructure. The latter is well captured using population density estimates but it is clear that an assessment of potential losses in the agricultural sector would need to be considered separately and would concentrate on the productivity or profitability of agricultural land. Unfortunately this is beyond the scope of this thesis.

It is clear from the review of potential exposure to flooding and landslides that existing geotechnical or hydraulic assessments in Ecuador are limited in their geographic extent. At the same time national level flood and landslide assessments remain simple or are compilations of maps of previous events. An additional shortfall with these assessments is the lack of complete metadata that would allow for their replication in other contexts or with new datasets for Ecuador. The advantage of the models developed here, by contrast, is that the methodology is clear and the data sources available which allows for subsequent modification. There are also problems of precision and accuracy with national level assessments such as the areas affected by flooding during the 1997-98 El Niño event (Instituto Nacional de Meteorología e Hidrología, 1999). Using these national assessments for a complete validation of the models developed in this chapter is therefore difficult and potentially unwise especially as a perfect fit between currently used evaluations of floods or landslides and the models developed in this chapter would suggest that the models were no improvement on those existing assessments. The more local spatial assessments of exposure or vulnerability to floods and landslide offer a good validation but for a limited spatial area, and the digital datasets are not available for all assessments. Validation of the flood and landslide models is preferable using observations of the areas affected as well as the impacts of the events in terms of people, or infrastructure affected. These observations are not always free of error or there is the possibility that the recorded events are biased towards urban or more accessible areas. There are also dangers in validating models designed for existing situation with observations from up to 40 years previous, due to changes in the location of the population. A more precise, georeferenced, publicly available inventory of both landslide and hazard events would be of great benefit for future activities in modelling these hazards.

The models developed in this chapter illustrate that national assessments of flooding and landslides are possible, and the primary data source allows for these models to be replicated in other countries. In order to be more useful and usable they would need to be modified using more precise data in their development as well as a better validation dataset. Nevertheless they are the first step towards an index of vulnerability that considers the capacity of the land and populace to cope with the damage associated with landslides and floods.

Chapter 5 : Creating an assets based vulnerability assessment

5.1 Introduction

This chapter considers vulnerability of districts to a reduction in household well-being as a result of floods and landslides caused by an El Niño event in Ecuador. The assessment of vulnerability developed here is based on the results and insights of the previous chapters. These investigated the importance of assets for household well-being in Chapter 2, the association of a previous El Niño event with changes in well-being at the district level in Chapter 3, and in Chapter 4 the development of models of potential exposure to floods and landslides. The key development in this chapter will be the investigation of the susceptibility of these assets, the spatial relationship between the location of assets and their exposure to floods and landslides, and the capacity of households and districts to cope with damages to assets.

A practical assessment of vulnerability of districts to the El Niño event implies a transparent (Kelly and Adger, 2000; Glantz, 2005) and intuitive (Metzger and Schröter, 2006) combination of the various components of the vulnerability equation (introduced in section 1.3.3). A good model for such an assessment is that for health, income and consumption indicators which are expressed as proportions of the population that are malnourished, or below a predefined poverty line, etc. These are widely used in Ecuador (Larrea et al., 1999; Instituto Nacional de Estadística y Censos, 2008) and a vulnerability assessment expressed in this way would be easy to understand. The assessment will therefore follow econometric assessments of vulnerability to poverty and will be expressed as the population vulnerable in each district.

The vulnerability assessment is based on a generic formula, which I have modified to consider the vulnerability of the smallest administrative area in Ecuador, the district. For each district *j* vulnerability is a function of the exposure of all households within the district to floods and landslides, the susceptibility of the assets on which the livelihood of each household *i* is dependent, and modified by the capacity of the households and district to cope with exposure to hazard. The term susceptibility is often used interchangeably with vulnerability or sensitivity in the literature, in this case I refer to the characteristics of an asset that make it more or less prone to damage as the result of exposure to a hazard.

$$\text{Vulnerability}_j = f\ \Sigma_j^{\ 1..i}[\text{exposure}_i, \text{susceptibility}_i, \text{coping}_i] \qquad (13)$$

The challenge is to produce a single figure for each district that incorporates the different levels of vulnerability of the constituent households. This challenge is further complicated by the fact that while models of exposure developed in Chapter 4 are at a relatively high resolution (every 90 m) the location of individual households is not known beyond an aggregation at the district level. I have therefore estimated the total population and the proportion of the population potentially exposed. This implies that the susceptibility and coping components of the vulnerability equation will also have to be treated at the district level, using summary indicators of the households to provide values for each district.

$$\text{Vulnerability}_j = f\ \Sigma_j^{\ 1..i}[\text{susceptibility}_i] * f\ [\text{exposure}_j, \text{coping}_j] \qquad (14)$$

The econometric models developed in Chapter 2 show which assets are significant determinants, or correlates, of household consumption. These models are only representative at the regional or sectoral (urban/rural) level, which makes it very difficult to incorporate spatial differences of susceptibility in the vulnerability equation. To assess the importance of these assets at the district level it is necessary to select those assets which can be mapped for individual districts based on household level census data.

While there are similarities between the root causes of ‘susceptible’ assets and the capacity to cope I will treat these two components separately in the following sections. These are followed by a combination of exposure, susceptibility and coping indicators and I conclude with a discussion of the results and the issues that arise.

5.2 Susceptibility of assets

The asset-vulnerability framework supposes that some assets are more important than others for sustaining a livelihood and contributing to household well-being. These significant assets are differentially susceptible and it follows that if a particular household is dependent on one kind of asset which is more susceptible than another then that household will be more vulnerable (all other things being equal).

This section explores the susceptibility of assets that contribute to household well-being outcomes, and proposes the spatial distribution of households based on a typology of their access to assets.

5.2.1 Spatially variable household asset profiles

The global, rural/urban and regional models developed in Chapter 2 demonstrate that the relationship between assets and well-being varies according to location. These models are representative at the regional or sectoral levels however, and do not allow the full variation in household asset profiles to be mapped and subsequently combined with spatially variable assessments of hazards associated with El Niño. A trade-off is therefore necessary between the depth and the spatial resolution of the profile. This implies that only those variables which are also available at high resolution can be included in a spatial assessment of susceptibility of assets; such a high resolution data source is the 1990 population and housing census.

Those variables which are found in both the census and survey are noted in the summary of the data used in the construction of the household and district models (Table 5). The number of variables is limited but the biggest drawback is that financial capital is not represented, and household level natural capital is only represented by agricultural workers. The significance of these assets in determining household well-being (Table 40) further limits the number of assets in the household asset profiles considered in subsequent sections.

Table 40. Standardised γ, and significance levels of selected explanatory variables in multilevel model with cross-level interactions.

		Urban	Rural
H1_EDUL_Z	+	0.013	**-0.021**
H2_LITS_Z	+	0.056*	0.087***
S1_TIME_Z	+	**-0.022***	**-0.039**
N6_AGWK_Z		-0.011	-0.044***
P1_NBED_Z	+	0.205***	0.205***
P2_ELEC_Z	+	0.073	0.022
NC1_DRY_Z	-	-0.091*	-0.031
NC2_LAND_Z	+	0.018	0.007
NC3_SLP_Z	-	-0.135***	-0.071*
NC4_NVEG_Z	+	0.098***	**-0.010**
PC1_ACC_Z	-	-0.049	-0.007
P1_NBED_Z *NC3_SLP_Z			0.043***

***significant at the 99.9% level; ** significant at the 99% level; * significant at the 95% level.

Figures in **bold** type indicate parameters with a sign different to that expected

5.2.2 Hazards associated with the El Niño event in Ecuador

Susceptibility of household and community assets depends to a great extent on the nature of the hazard to which they are exposed. This study concentrates on the events that accompany an El Niño phenomenon, and I make reference to the hazards that were associated with the El Niño phenomenon of 1997-98 since this was a large well documented event.

The direct effects of the El Niño event of 1997-98 were higher air temperatures, reduced solar radiation, higher sea surface temperatures and lowering of thermocline. In addition higher annual, seasonal, monthly and daily precipitation totals as well as the intensity of rainfall events (Dirección Nacional de Defensa Civil, 1998) were experienced in Ecuador.

These phenomena led to secondary effects, particularly the saturation of soils leading to landslides, and the flooding of land where rivers were breached (Dirección Nacional de Defensa Civil, 1998). It is these secondary effects that damaged buildings, and caused the loss of human life and crops. Flooding and landslides were also responsible for the damming of water sources and contamination from agricultural, industrial and residential sources leading to increased turbidity, creating spawning grounds for vectors of diseases, as well as bacteria and diseases (Corporación Andina de Fomento, 2000; Ministerio de Salud Pública, 1998).

5.2.3 Susceptibility of assets significant to household well-being

Here I assess the innate susceptibility of different assets to damage due to natural hazards, specifically to flooding and landslides associated with the El Niño event. Only those assets that are susceptible to floods and landslides will be considered in the susceptibility component of the vulnerability equation.

Six household level assets included in the multilevel well-being models are also captured in the 1990 household and population survey (Table 40) but I will concentrate on the assets that were significantly correlated with the dependent well-being variable: literacy, time in the community, proportion of agricultural workers, and the number of bedrooms. Similarly, for the five district level contextual variables included in the multilevel models I concentrate on those that were significant: the number of consecutive dry months, the percentage of the district covered by natural vegetation, and the maximum slope.

Literacy is a human capital asset which in itself is unlikely to suffer as a result of the impact of El Niño, unlike other characteristics of individual humans such as physical strength that can be affected by illness. Nevertheless a household is susceptible to loss of literacy whenever a literate household member is killed due to exposure or if the individual has to move away and is no longer able to contribute to the household well-being by virtue of his/her literacy. Susceptibility of individuals to direct exposure to flooding and landslides or to diseases depend on the existing health status of the individual household members, as well as the differential likelihood of exposure, for instance the prevalent location of livelihood activities may differ between offices, fields or the home. This exposure to hazards is also likely to be related to the choice of livelihood activities available to a household, where poorer households have less choice of avoiding exposure (Chambers, 1989).

Time in the community was shown to be negatively associated with household well-being and may be more a consequence of poor levels of well-being, rather than a contributor. For example a family with few options but to stay in the area they know and continue with their traditional activities. This kind of asset may be susceptible to change as a result of exposure to natural hazards such as flooding or landslides, if families are forced from their communities to other locations. It is not clear, however, whether this would improve household well-being.

The proportion of workers in a household who are engaged in agriculture is negatively associated with well-being, i.e. if the number of agricultural workers goes up then well-being reduces. A household is therefore vulnerable to reduced well-being if workers in non-agricultural sectors are forced to move into agriculture as a result of a natural hazard like El Niño. The conditions for this occurrence could include the disruption of transport infrastructure reducing access to urban areas, or if there is a loss of employment opportunities outside of agriculture. Meanwhile if agricultural employment is affected then it does not imply that workers will be able to find employment in other sectors (I assume here that agricultural work is the least attractive).

The number of bedrooms per person per household is a difficult asset to consider and as discussed in Chapter 2 the causality is unclear. I assume in the models, however, that the number of bedrooms per household is an indicator of overcrowding, and that fewer people per bedroom improves the well-being of the household members. The corollary is that if the number of bedrooms decreases – say due to damage to the structure of the dwelling – then the well-being of the household will be negatively affected.

Dwellings are differentially susceptible to the direct effects of floods and landslides according to their design and the quality of the materials used in their construction.

In industrialised countries a mature insurance services industry means that susceptibility has been monitored over time and partially as a result of increasing damages (Johnson et al., 2007) has been explicitly considered in household insurance policies (Thieken et al., 2006), and incorporated in building codes. Details of these codes include materials resistant to damage, the design of buildings (e.g. the location of doors and windows or the inclusion of flood shutters), as well as the location within buildings of susceptible assets (Simonovic, 2002; Kreibich et al., 2005). Indigenous adaptation to hazards are also a characteristic of coastal Ecuador where buildings are often constructed using large bamboo canes and where the living quarters are elevated and the space below used for storage (Parsons, 1991).

Turning my attention to the district level variables, the number of consecutive dry months is directly susceptible to climatic events like the 1997-98 El Niño phenomenon. The amount of rain which fell in that period would have altered the availability of water, but since the variable is negatively correlated with well-being then an increase in availability could improve well-being. Alternatively if the inhabitants are unused to the amount of precipitation then it could have caused problems especially for areas dependent on agriculture.

The variable for the maximum slope is not susceptible to changes at the district scale to exposure to events such as flooding and landslides. Local changes may occur due to landslides, but these are unlikely to change the topography of a whole district.

The percentage of the land area in a district which has unprotected natural vegetation is a significant determinant of well-being for urban households. However this variable is unlikely to be susceptible to changes due to floods or landslides associated with the El Niño event. Another asset, the accessibility to provincial capitals, relies on physical infrastructure and is likely to be susceptible, however this asset is not a significant correlate of well-being for households in either the rural or urban sectors.

I have shown that human and physical capital assets are both important for household well-being and susceptible to exposure to hazards associated with El Niño events such as flooding and landslides. This implies that districts which have many households that have high levels of these assets may also be susceptible to reductions in well-being as a result of flooding and landslides.

5.2.4 Household typology of susceptible assets

Applying the coefficients of the variables to the data in the 1990 population census will give a nationwide map of consumption estimates similar to those produced by Larrea et al. (1996). Given the context of this study the household data from the population census can instead be used to map those areas with households that rely more on particular types of assets.

I construct a typology of households based on a comparison of their assets to the values for other households in similar contexts. Using household assets to create types of households or farms is a common approach to allocating households into domains that can be used for further analysis or for policy recommendations (e.g., de Janvry and Sadoulet, 1996; Davis and Stampini, 2002; Maltsoglou and Taniguchi, 2004).

Households in the rural and urban sectors are categorised according to a comparison to the sectoral and regional average values of the literacy rate of household members and the number of bedrooms per adult equivalent household member. These are then combined to give a typology of 4 household types (Table 41).

Table 41. Combination of significant assets to create a household typology

	Bedrooms below average	Bedrooms above average
Literacy below average	1	2
Literacy above average	3	4

Of particular interest are household types 2 and 3 which show a greater contribution of one asset than the other. Districts are subsequently classed according to the most common household type. It is clear that there are far more districts with a majority of households that have levels of literacy above the mean for their respective region and sector[53] (Table 42). Similarly most households do not rely disproportionately on literacy or their bedrooms to sustain their livelihoods.

Table 42. Most common household types per district

Most common household type	Frequency	Percent
1	75	8.2
2	43	4.7
3	229	25.3
4	564	61.8
Total	911	100

The spatial patterns show that districts comprised of households with greater than average literacy and fewer than average bedrooms are found in all regions but are particularly concentrated in the southern and central coastal region, as well as clusters in the extreme south and north of the Andean region (Figure 54). The few districts with a majority of households with a typology of low literacy and large dwellings are scattered in the central Andes and the northern coastal region.

[53] Due to the binomial and skewed distribution of the literacy variable

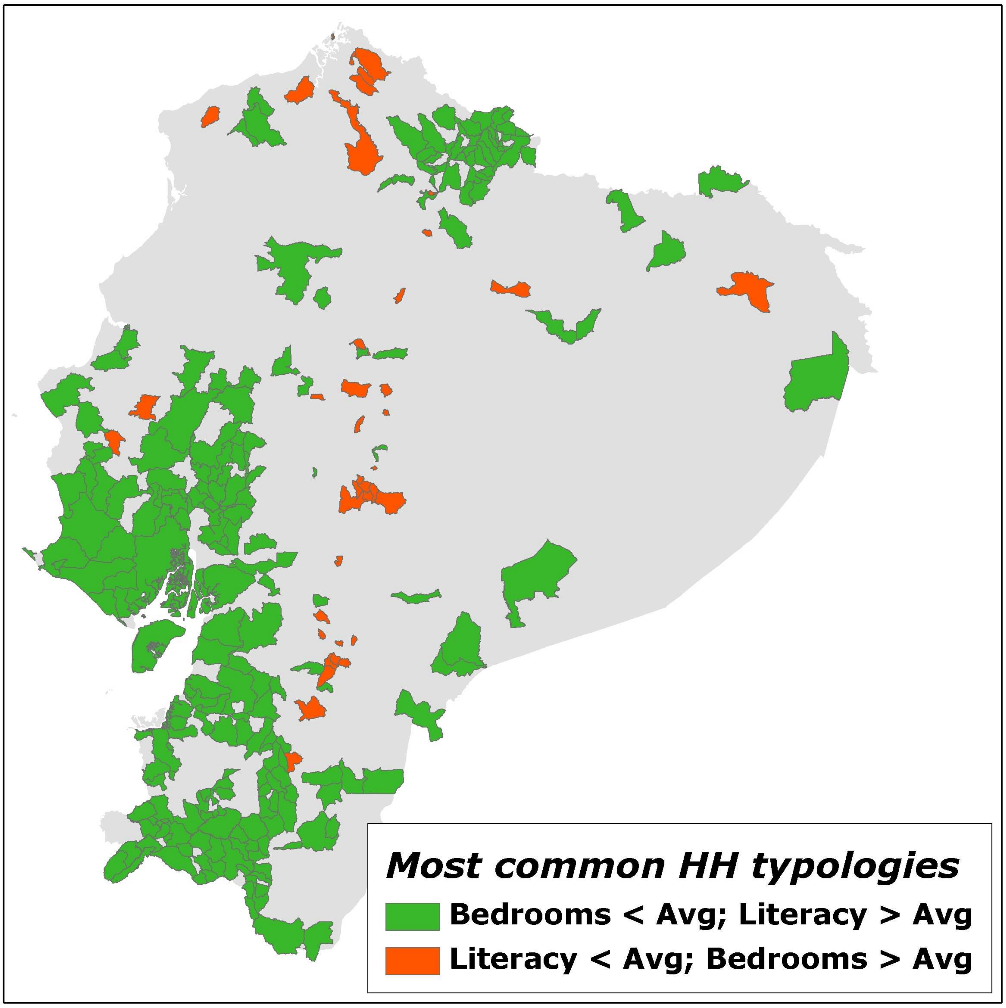


Figure 54. District summaries of household typology based on combination of household values for literacy, access to electricity and number of bedrooms per household member

5.3 Capacity to Cope

The final component of the vulnerability equation is the capacity of the household and the district to cope with a natural event such as El Niño. Coping strategies have been most commonly studied in famine situations (e.g. Frankenburger and Goldstein, 1991; Maxwell et al., 1999), but also for events that effect infrastructure and which imply an institutional as well as a household response (e.g. Adger, 1999; Sales Jr, 2009). Coping strategies are not limited to the mechanisms or activities which follow a shock but can also comprise the measures taken before a shock to reduce exposure or mitigate damage. Baez and Mason (2008) consider risk management and coping to be *ex ante* and *ex post* measures of short duration, which implies that risk management should be considered as part of coping in the general vulnerability equation. Examples of risk management are: savings, insurance, precautionary actions, migration, income diversification, and collective risk sharing. Ex post coping include: borrowing, reducing consumption, trading assets, labour supply adjustments, income diversification, migration, transfers and social networks (Baez and Mason, 2008; CARE/WFP cited in Devereux et al., 2004; Vatsa, 2004; Eakin, 2005; Tesliuc and Lindert, 2003; Barrett et al., 2001; Alwang et al., 2001; Moser, 1998; Maxwell and Frankenburger, 1992).

5.3.1 Indicators of capacity to cope with natural events

Measures of coping strategies should allow for the differentiation between districts of their capacity to plan for and respond to the floods and landslides (and secondary effects) of a future El Niño event in Ecuador. The measure ought to include a household component and should also take into account district level capacities (Adger, 1999).

The ability of a household to invest in risk management strategies is linked to its access to resources, for which the district poverty level is a proxy (Baez and Mason, 2008; Adger, 1999). At the same time Moser (1998) links resilience in the face of threats to the amount and quality of assets and entitlements that a household possesses or can mobilise. This and other studies (e.g. Tesliuc and Lindert, 2003) suggest that an indicator based on ‘direct’ measures of access to basic needs that help households cope – such as access to housing, electricity, and water – is preferable to poverty. These basic needs are often collected during the population and housing census and so allow for the creation of district level summaries.

Household relations and general social capital, are important components of coping and have been recognised in many contexts and studies (Adger, 2003). Moser (1998) contrasts the highly commoditised livelihoods of populations in fragmented urban settings, with those in rural areas where there is often a moral economy enabling households to draw on assistance from neighbours. Baez and Mason (2008) note, however, that some community risk management mechanisms are less effective when the shocks are covariate (such as a natural hazard like floods). Adger shows that social capital, and in particular the institutions active at different levels, can have a significant role in the effectiveness of strategies for coping with natural hazards. The relative difference in performances of institutions is one of the few non-household variables that can be considered in the analysis of district-level vulnerability.

5.3.2 Indicators of coping with El Niño in Ecuador

The state has a limited and historically confused role in Ecuadorian disaster management (Solberg et al., 2003), and local leadership is recognised as being of some importance (Andrade, personal communication in Farrow, et al., 2002). Disaster contingency plans have been prepared, and show areas likely to be exposed to flooding and landslides, but as seen in Chapter 4 these plans are restricted to urban areas, are not accompanied by mitigation efforts (Olson et al., 2000), and differ according to each institution (Vásquez, 2005). The civil defence organization is responsible for dissemination of forecasts, and the rescue of people affected by exposure as well as disaster preparedness exercises. The institutions responsible for responding to future crises are unlikely to have a clear mandate and since the 1998 constitution the state is devolving many powers to local government (Andolina, 2003), albeit slowly and in some cases inefficiently (Faust et al., 2007; Cameron, 2005). All of these factors contribute to the situation whereby data on institutional effectiveness is either not collected or not available.

Similarly, section 2.2.3.2 showed that community-level social capital indicators are not available from the ECV, a situation repeated for other potential sources of data.

While information on social capital and institutional effectiveness or investment is lacking for Ecuador, data on household basic needs, consumption and poverty are available (Instituto Nacional de Estadística y Censos, 2008). The unsatisfied basic needs (UBN) index is calculated for all households in the 2001 population and housing census and summarised for each district[54]. The index incorporates 5 indicators: (i) poor housing materials; (ii) inadequate water or sewage services; (iii) highly economically-dependent households[55]; (iv) households where children between the ages of 6 and 12 do not attend school; and, (v) households that share a bedroom between three or more people.

A similar index has been created by the World Food Programme (WFP) in Ecuador to help focus their food aid distribution efforts in areas with high proportions of households ‘at risk’ (Moreano, personal communication, 2004). The WFP index has five categories from ‘no risk’ to ‘highest risk’, and is composed of the UBN index as well as health assistance indicators such as the number of doctors, nurses, and clinics in the district. This additional information serves two purposes, firstly the provision of health services might be vital for protecting human capital assets, and secondly there is some evidence, albeit at the national scale, of a link between corruption and expenditure on health (Mauro, 1998).

The major spatial differences between the UBN index and the WFP risk index can be seen in the central coastal region where there are numerous districts with high levels of unsatisfied basic needs but with low food security risk levels (Figure 55). The eastern Amazon region, in contrast, has higher risk levels despite lower levels of unsatisfied basic needs – these differences are due to the lack of health personnel and infrastructure in the Amazon region.

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[54] The household level data are not publicly available
[55] Any household with 3 or more persons per occupied member, where the household head has 2 years or less of primary education

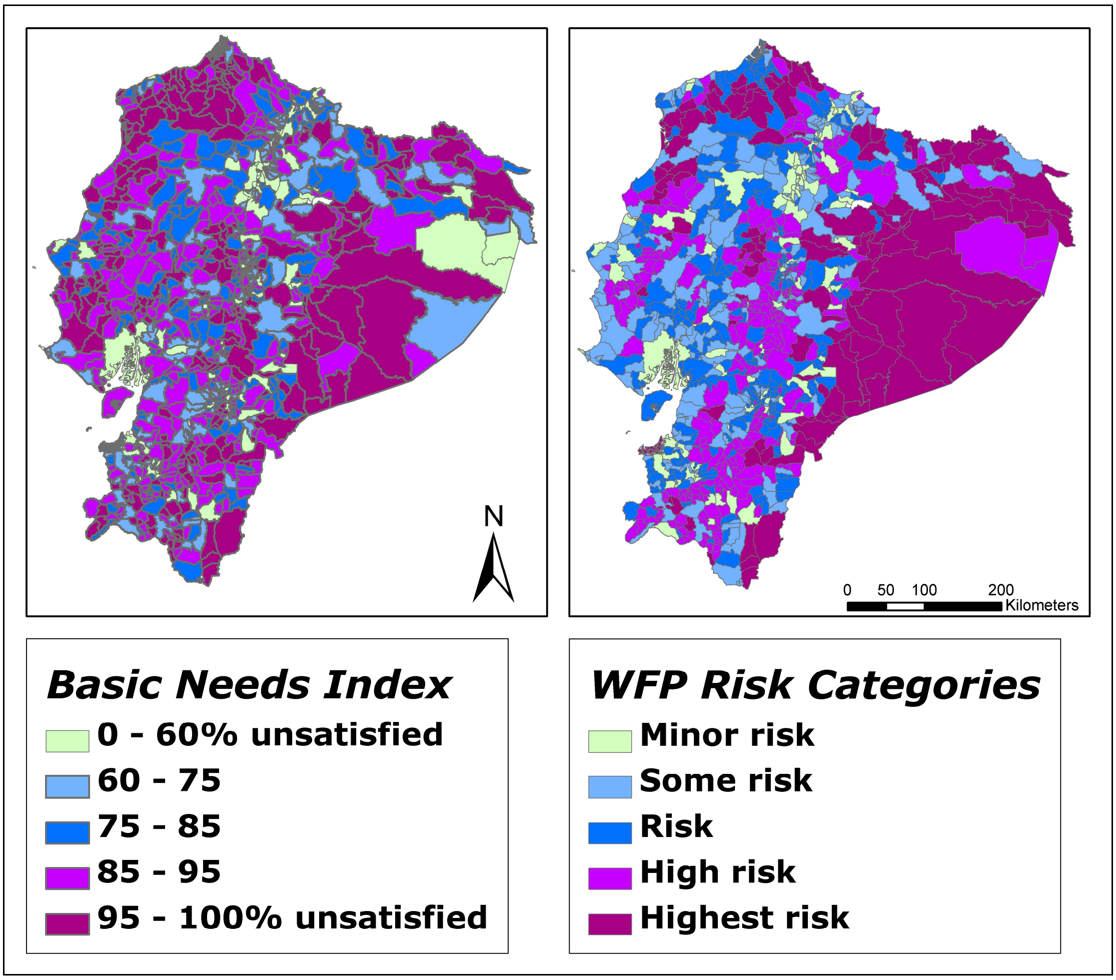

Figure 55. Distribution of percentage of households with unsatisfied basic needs (UBN) per district, and risk categories of districts based on UBN and health services.

The exact methodology used by WFP to create the risk index has not been published and it is unclear how the health infrastructure is used to adjust the UBN figures, this can be seen in (Table 43) where the summaries for the health indicators are shown for each risk category.

Table 43. Summary of Medical personnel per '000 people (Landscan 2006) for WFP risk categories

WFP risk category	n	Mean	Std. Deviation	Minimum	Maximum
Minor risk	97	3.45	3.14	.00	14.21
Some risk	215	3.43	18.20	.00	260.87
Risk	273	2.40	5.64	.00	57.14
High risk	274	5.16	23.90	.00	333.33
Highest risk	121	11.01	45.06	.00	454.55
Total	980	4.58	22.38	.00	454.55

The average values for UBN for each risk category show that the WFP and the unsatisfied basic needs indices are aligned (Table 44). However it is apparent that there are some districts with a UBN value of 100[56] that are not in the highest risk class due to better health services available. At the same time there are districts with a relatively low UBN[57] that are in the highest risk class due to the poor health services.

Table 44. Summary of Unsatisfied Basic Needs Index for districts within each WFP risk category

WFP risk category	n	Mean	Std. Deviation	Minimum	Maximum
Minor risk	97	50.1	10.8	25.9	73.5
Some risk	218	74.3	9.3	47.5	98.1
Risk	280	87.4	7.3	61.4	100
High risk	275	92.5	6.6	49.0	100
Highest risk	124	95.4	7.7	53.5	100
Total	994	83.3	15.4		

Due to the fact that the WFP risk categories at the district level are not clearly explained I will use the simpler unsatisfied basic needs index as the proxy for coping and risk management in the vulnerability equation.

5.4 Combining exposure, susceptibility and coping

I express vulnerability as the percentage and total population vulnerable in each district to reductions in well-being. The assessment combines exposure, susceptibility, and coping, and can be considered as a continuum between two extremes of vulnerability (Table 45).

[56] Signifying that the basic needs of 100% of households in the district are unsatisfied
[57] e.g. Pañacocha district in the Amazonian Sucumbios province with 53.5% of households with unsatisfied basic needs.

Table 45. Extremes of the district-level vulnerability to floods and landslides associated with the El Niño event

Exposure	**Susceptibility**	**Coping**
Worst case		
100% of the population potentially exposed to floods and/or landslides[58]	Households particularly dependent on assets susceptible to damages from floods or landslides	100% of households lacking basic needs
Best case		
Low proportion of population potentially exposed to floods and/or landslides	Not particularly dependent on assets susceptible to damages from floods or landslides	Low percentage of households lacking basic needs

Combining these components at the district level requires a specification of the functions used in the vulnerability equation (Equation 14).

$$\text{Vulnerability}_j = f\ \Sigma_j^{\ 1..i}[\text{susceptibility}_i] * f\ [\text{exposure}_j, \text{coping}_j]$$

Some authors (such as Alwang, 2001 or Connor, 2005) suggest that the components are additive or subtractive, whereby vulnerability is the exposure multiplied by the susceptibility and then subtracting the coping. However I have shown that the coping strategies used by households and districts are not only reactive, adaptive or recuperative measures but also include risk management which serves to reduce either the exposure or the susceptibility of assets to exposure to floods and landslides (and secondary effects). This implies that the combination of the components in the vulnerability equation is multiplicative.

Exposure is expressed in the percentage of the population exposed to different flood and landslide scenarios (Section 4.4.3). Capacity to cope is expressed as a summary of households' access to basic services. These summaries can be applied easily to the levels of exposure such that the percentage of the population exposed (to both floods

[58] Landslide and flood populations are added, there are very few areas where the population is potentially exposed to both hazards

and landslides) is modified by the percentage of households with unsatisfied basic needs.

The contribution of the susceptibility component within the vulnerability equation is the least certain and does not easily lend itself to the calculation of a final value of the population vulnerable. The susceptibility will be assessed qualitatively and will be used as a narrative modifier to the other components of the equation (Metzger and Schröter, 2006). The vulnerability equation that I use for mapping is:

$$\text{Vulnerability} = (\text{\% population exposed} * \text{\% population with unsatisfied basic needs}) * f\,(\text{susceptibility}) \tag{15}$$

The results of the application of the vulnerability equation (Equation 15) to the districts of Ecuador are best viewed on a map which shows the population vulnerable[59] overlaid with the household typology[60] (Figure 56).

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[59] Which is the % population exposed * % population with unsatisfied basic needs
[60] Which represents districts with many households that are particularly dependent on susceptible assets.

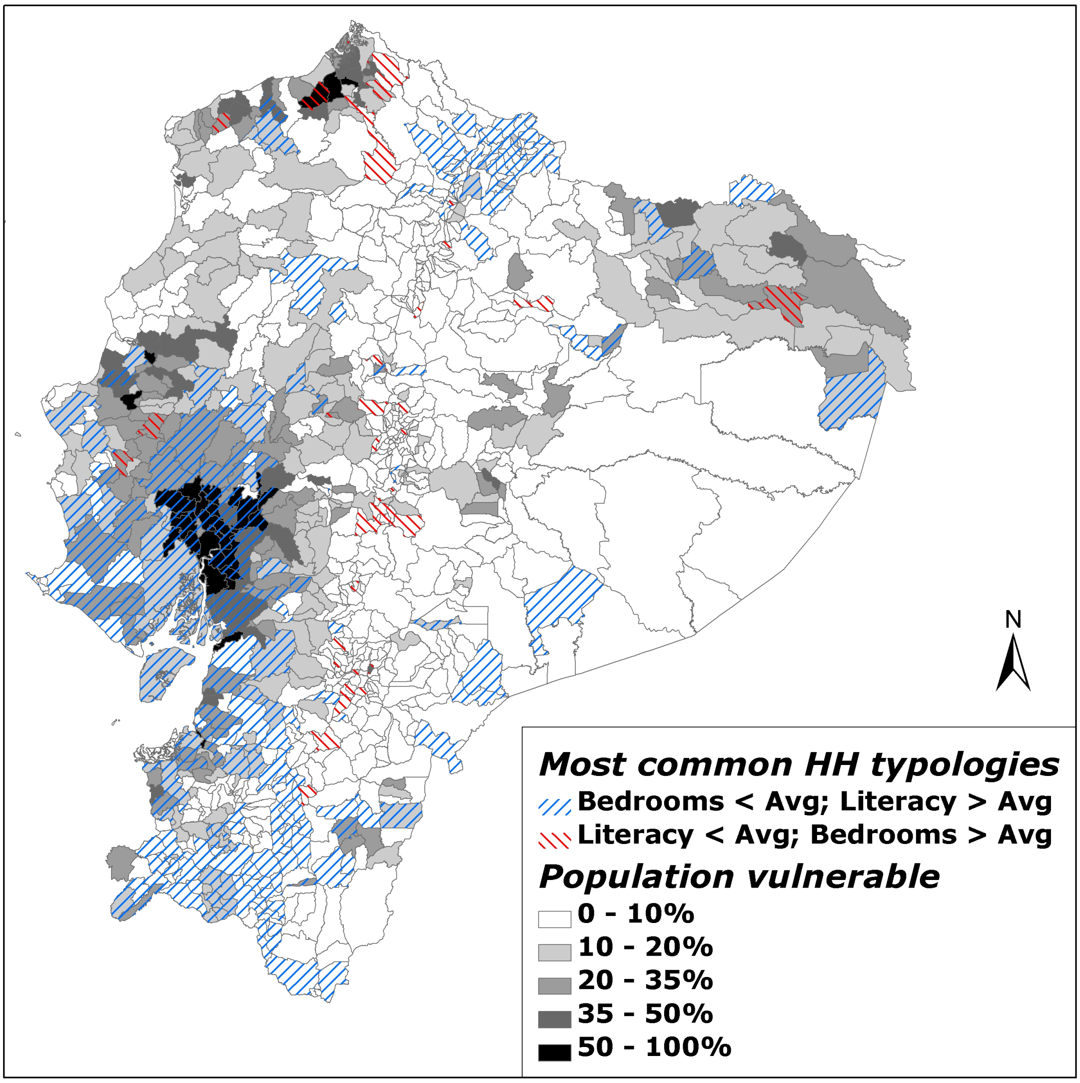

Figure 56. Percentage population vulnerable per district.
Combination of exposure and coping (to give the population vulnerable) and susceptibility to produce a flood and landslide vulnerability assessment for Ecuador expressed as percentage population vulnerable.

The vulnerability assessment shows that the districts with the greatest percentage of the population vulnerable to floods and landslides associated with the El Niño event are concentrated in western Ecuador in the central Coastal region in the lower Guayas basin. Further clusters are observed in central Manabí province and in Esmeraldas province. There are also a number of districts in the northern Amazon region that are potentially vulnerable. Many districts in the lower Guayas basin are characterised by households that have high levels of literacy but lower than average number of bedrooms – suggesting a dependence on human capital assets. In contrast in Esmeraldas there are a number of districts that have few people per bedroom but experience low literacy levels. These are districts that might be vulnerable to damage to the physical infrastructure of households.

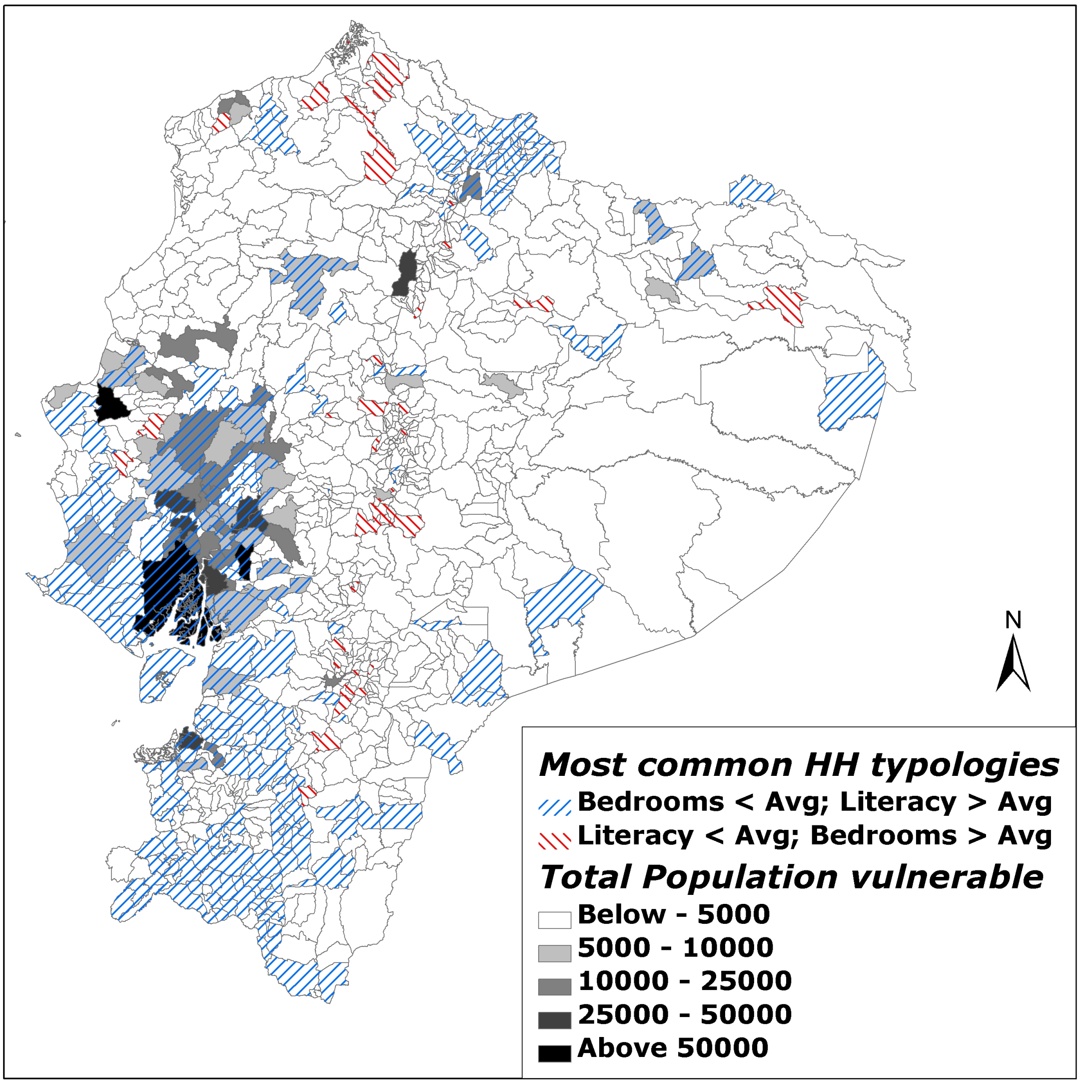

Figure 57. Total population vulnerable per district.
Combination of exposure, and coping (to give the population vulnerable) and susceptibility to produce a flood and landslide vulnerability assessment for Ecuador expressed as total population vulnerable.

When expressed as the total population within each district vulnerable to floods and landslides the districts in Esmeraldas province do not appear as priority areas. Instead the major cities and towns of Ecuador are most obvious (Figure 57). The map shows that districts which have many households susceptible to physical or infrastructure damages have relatively few people vulnerable to floods and landslides associated with the El Niño event.

The combination methodology presented here is sensitive to the assumption that the unsatisfied basic needs index is spatially random within the district. Given a district where 50% of households are exposed to floods and landslides and 50% of the households have unsatisfied basic needs it is possible that all of the exposed households have unsatisfied basic needs or equally possible that none have unsatisfied basic needs. To explore this sensitivity I produce two scenarios – one which represents the maximum percentage of vulnerable households[61], and the other for the minimum number of vulnerable households[62] (Figure 58).

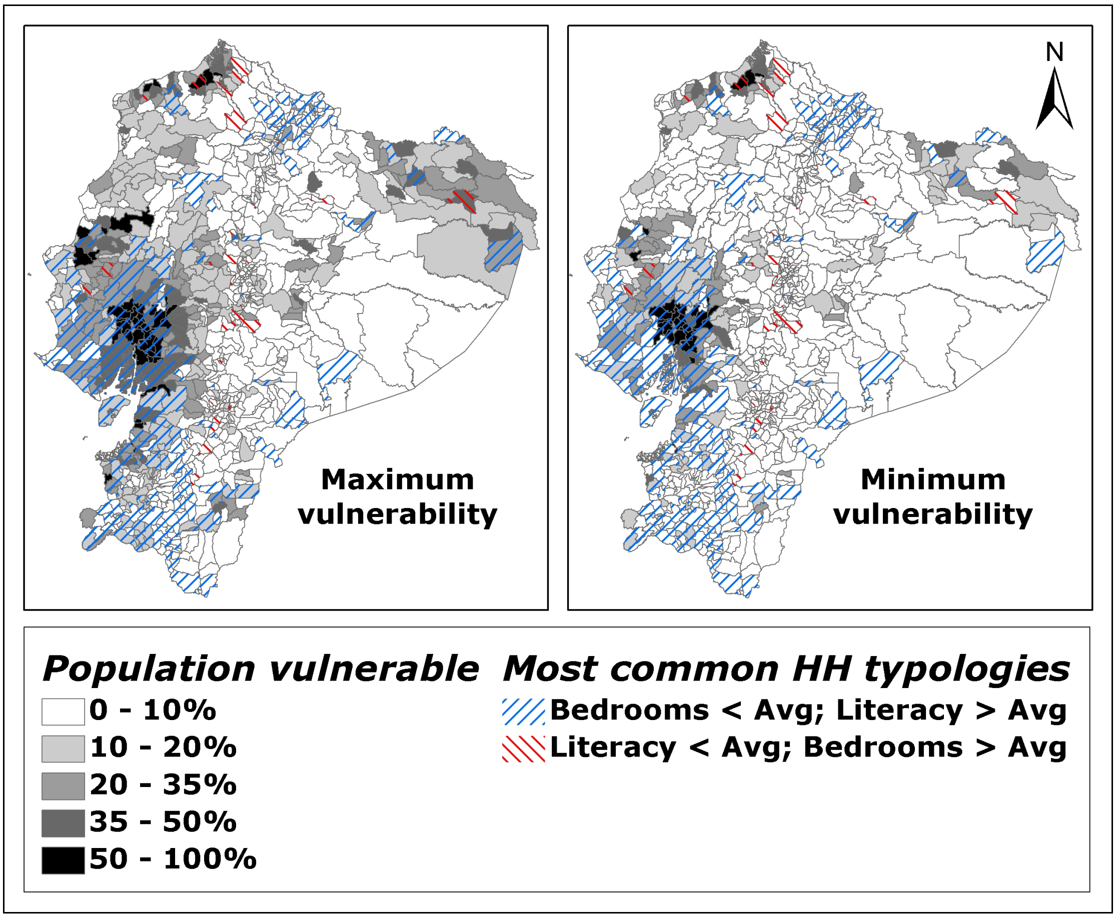

Figure 58. Maximum and minimum vulnerability values for Ecuador expressed as percentage population vulnerable

These maps of the range of percentage of vulnerable households show that the clusters of districts in the lower Guayas basin and in northern Esmeraldas are highly

[61] This is calculated as the lesser of the district values for % UBN and % exposure
[62] This is calculated as % UBN + % exposure – 100, where negative numbers are given a value of 0%

vulnerable for both scenarios. These are districts with very high values for exposure, UBN, or both. In contrast some parts of the central coastal province of Manabí display a large range of possible percentages of vulnerable households; districts such as Portoviejo and Chone are characterised by values of exposure and UBN close to 50%. While neither the maximum nor minimum scenarios are likely, they provide a useful addition to the vulnerability assessment and help in the interpretation of the maps (Figure 56).

5.5 Discussion of findings

This chapter brings together the three major components of the vulnerability equation that I use as a guide to assessing vulnerability to the El Niño event in Ecuador; namely exposure, susceptibility and coping. The focus on household level well-being and assets enables a logical approach to defining a function for combining the three components. More specifically the expression of district levels of vulnerability in terms of the total number of people, and the proportion of the population that are vulnerable is a conceptual improvement on previous efforts to assess vulnerability in Ecuador (e.g. Vos et al., 1999; Demoraes and Dercole, 2001). In addition the assessment presented here benefits from more recent and more accurate maps of potential exposure, and incorporates an element of coping that has been missing from previous assessments. Most importantly the assessment can be used in decision making arenas and is transparent.

Three important issues are raised in this chapter: (i) the importance of assets within the Sustainable Livelihoods framework; (ii) scale issues due to the mixing of data from multiple scales and ecological fallacy, and; (iii) overcoming the problems of availability of data.

Given the data available I show that a reasonable approach is to consider the susceptibility of assets at the household level and create typologies of households based on their asset profiles. The diversity of household types within the typology is somewhat limited. This is unavoidable given the small number of variables that are clearly susceptible to landslides and flooding and that were collected in both the 1995 ECV and the 1990 population and housing census. It can also be contested that the asset values in themselves do not accurately portray dependence on a particular asset, especially since threshold reference points (such as those used by de Janvry and Sadoulet, 1996) are not obvious for either asset. A further difficulty is the incorporation of the susceptibility of these assets, households and finally districts within the vulnerability equation.

Assets are just one component of the sustainable livelihoods framework (or the household access framework [Blaikie, 1994]). Other approaches to mapping vulnerability focus on the identification of vulnerable groups based on their livelihood activities and strategies (Vos et al., 1999; Adger, 1999), or on their innate susceptibilities (such as children, elderly or female-headed households [Jaspers and Shoham, 2002; Amin et al., 1999 cited in Kamanou and Morduch, 2002]). These approaches look at the susceptibility of assets in a more holistic manner than the econometric approach undertaken in my research and may yield more relevant results for inclusion in the vulnerability equation. The construction of livelihood profiles (e.g. Boudreau, 2007) might be possible using the household data available in the ECV surveys. These profiles allow an assessment of the diversity of income or nutrition sources in representative households, which are differentially susceptible to hazards. However, given the coarse representativity of the ECV domains, local knowledge from almost every part of the country would be needed to produce livelihood zones – which is beyond the scope of this thesis.

The combination at the district level of exposure to floods and landslides, unsatisfied basic needs, and most common household typologies mixes various units of analysis and spatial scales. This raises the possibility of inferring relationships which are in fact spurious and purely artefacts of the aggregation of individual households – a problem known as ecological fallacy. Ecological fallacy is the attribution of group characteristics to individuals within that group, and inferences on the association with other group characteristics (Robinson, 1950). In my study I make the assumption that the rates of unsatisfied basic needs and the distribution of households as typified by their asset profiles are not spatially dependent within each district. Given that the census data from which the UBN and asset profiles are derived are already referenced at the lowest administrative unit the only solution to this problem would be through the geo-referencing of individual households, which is a highly unlikely scenario. Thus the approach adopted here – to test the sensitivity of the results to the assumption of spatial non-dependency – is the most appropriate, and allows the identification of districts for which the vulnerability values are more sensitive than others.

Lack of access to data is a constraint for all three components of the vulnerability equation but is most evident in the creation of district level values for coping capacity. The indicator chosen to represent the coping capacity of households and districts - percentage of households with unsatisfied basic needs – is an acceptable measure of household access to resources for *ex ante* and *ex post* coping. However there are no data available on the social and institutional capacities. Rural and urban households are considered in the household asset profiles and typologies but the importance of location for social capital is not clear and further research in Ecuador is needed to assess the relative importance of the rural 'moral economy' (Pelling, 2003; Moser, 1998) vs. urban access to more formal institutional responses (Drèze and Sen, 1989).

All of these conclusions point to the need for validation of the components of the vulnerability equation, i.e. the importance of assets to households and the susceptibility of those assets, the spatial distribution of hazards associated with the El Niño phenomenon, the importance of social capital and institutional effectiveness in times of exposure to hazards, and the longer term impacts of the El Niño phenomenon on household well-being in Ecuador. These are explored in the following chapter.

Chapter 6 : Validation of an assessment of vulnerability to El Niño in Ecuador: a case study of 4 areas in the province of Manabí

6.1 Introduction

The first objective of this chapter is to validate the calibration and construction of the asset-well-being models focussing on households and communities in four areas of the coastal province of Manabí, a province affected by most El Niño events (Rossel, 1999). The second objective is to validate the associations found between changes in welfare during the 1990's and the 1997-98 El Niño event. In particular I seek to clarify if the relative deterioration in household consumption and relative increase in poverty in the coastal region were linked to the impacts associated with El Niño and whether prior experience of events, household assets, or external assistance ameliorated the impacts.

The third objective is to compare the flooding and landslide events that occurred during the 1997-98 El Niño event with the flood and landslide models that I have developed, in effect ground-truthing the models using a sample of households in 4 areas in Manabí.

6.1.1 Validation Objective 1

The asset-well-being models were developed in Chapter 2 to help investigate the links between assets and household consumption. The choice of assets follows the sustainable livelihoods framework whereby assets are grouped according to five capitals: human, social, physical, financial and natural. The analysis of the model results show that it is difficult to say definitively that a particular group of capitals is more important, or that there are large regional differences between the contributions of a particular household asset to consumption. In this chapter I will therefore capture and analyse primary data to help determine the importance of different capitals in coastal Ecuador in maintaining well-being and as an asset that can be drawn on for risk management and post-event for either coping or adaptation. This information can be used to inform the calibration of models such as those developed in Chapter 2 on the relationships between assets and well-being.

Specifically this survey will explore the hypothesis that different assets within the sustainable livelihoods framework are more important than others for their influence on household well-being.

6.1.2 Validation Objective 2

The associations between the impacts of the 1997-98 El Niño event and changes in well-being, while generally positive, displayed differences in strength, depending on the indicator chosen for impact and well-being (see Chapter 3). More information is required on the experiences of households in areas that were affected by the 1997-98 event, and the effect of El Niño on their well-being. In addition the information collected should inform the assessment of vulnerability carried out in Chapter 5 with the perceptions of respondents on why damages were incurred and the susceptibility of different assets, such as homes, or crops, to floods and landslides. The information collected will record the strategies used by households to cope with the immediate and longer terms impacts of the El Niño phenomenon, especially the damage to household assets for which there is a purported relationship with household well-being. The survey will also ask respondents about the prevention measures put in place by external organizations and their response during and after the 1997-98 El Niño event. Due to a lack of data the role of external organisations in helping households cope with the effects of shocks such as floods and landslides was not an aspect that was considered in the vulnerability assessment. In a large province like Manabí the institutional response to extreme climatic effects is likely to be patchy with the state unable to respond in all areas especially, for covariate events (see Tesliuc and Lindert, 2001, Thomas, 2003 and Skoufias, 2003 for examples) that affect many people at the same time, like El Niño.

I have formulated three hypotheses based on the conclusions of previous chapters and on studies in Ecuador and elsewhere. The first hypothesis is that the well-being of those households that suffered damages in the 1997-98 El Niño was more negatively affected than those who suffered less. Linked to this is the hypothesis that the long-term impact of the 1997-98 El Niño event will be worse for those households or communities that have fewer assets. The final hypothesis is based on the concept of the development of adaptive capacity and states that the impact of the 1997-98 El Niño event will be worse for those households or communities that have little experience of previous heavy rainfall events.

6.1.3 Validation Objective 3

The third objective of this chapter is to validate the flood and landslide models developed in Chapter 4. The objective is not to explore a particular hypothesis, instead the different flood models will be compared with the recollections of exposure to, and damages caused by, actual floods and landslides which occurred during the 1997-98 El Niño event.

6.2 Methods and materials

The validation of the vulnerability assessment of districts in Ecuador to the El Niño event will address the assumptions of the importance of assets in well-being, the exposure to natural hazards, the coping strategies of households who are affected by flooding and landslides, and the longer term impacts of El Niño events. Given the complexity and inter-relationship between these issues the methodology for data collection and analysis is a mixture of quantitative and qualitative. The approach for collecting data follows that of Hentschel and Waters (2002) and employs a household survey using a structured questionnaire augmented with key informant interviews, and followed by focus group discussions.

Focus group discussions, with their roots in market research, have a long history in the qualitative investigation of phenomena. In the natural hazards literature they have been used to gauge respondents' levels of preparedness (e.g. Diekman et al., 2007), to document descriptions and perceptions of the events (e.g. Moore, 2004; Tapsell et al., 2002), and to assess the longer term impacts and recovery from hazard events (e.g. Pfefferbaum, 2008; Sartore, 2008). Focus groups have also been employed to appraise citizen involvement in the planning of mitigation efforts for natural hazards (Mitchell, 2003). The focus group discussions are not carried out simultaneously with the household survey; instead they were convened 9 months after the original survey to allow for preliminary analysis. In this sense the focus group discussions are designed as a tool for recording the community experiences of the 1997-98 El Niño event and for discussing the results of the household responses rather than for providing material for the survey (cf. Barrett, 2001).

The location of the interviews and focus group discussions are recorded using handheld GPS receivers[63] allowing a comparison with the flood and landslide models developed in Chapter 4.

6.2.1 Study area

The coastal province of Manabí was chosen due to the fact that Manabí suffered seriously in terms of the number and severity of landslide and flooding incidents during the 1997-98 El Niño event (see section 3.2.2), and previous surveys which had highlighted El Niño as an issue (Mera, personal communication, 2001).

The sampling frame for the primary data collection is based on the validation objectives and the associated hypotheses. The sampling frame takes into account a number of criteria for climatic history and impacts. Four scenarios are envisaged (Table 46): (a) this area has historically experienced El Niño but did not suffer in the 1997-98 event; (b) this area has experience of El Niño and suffered badly; (c) this area historically did not experience El Niño and did not suffer in the 1997-98 event, and; (d) this area has little experience of El Niño but suffered the effects in the 1997-98 event.

Table 46. Proposed matrix for sample locations

	Did not suffer	Suffered badly
Historically experienced El Niño	**a**	**b**
Little experience of El Niño	**c**	**d**

[63] Giving a horizontal error of ± 15m

Indicators of the effects of the 1997-98 El Niño event are discussed in detail in Chapter 3. The indicators of vulnerability (Vos et al., 1999) to agricultural losses and health risks, do not show differences between different El Niño events while the database of reported incidents (DesInventar, 2004) implicitly includes aspects of susceptibility, given that flooding or landslide incidents where no-one was affected is unlikely to be reported in the sources used for the DesInventar database.

Maps of exposure to flooding have been created for both the 1997-98 and the 1982-83 El Niño events and the deficiencies in these maps are discussed in both Chapters 3 and 4. In the province of Manabí there are differences in the areas flooded in 1997-98 and the previous extremely strong event but these differences are likely due to differences in the methodologies used to create the maps. I therefore use precipitation anomalies as my indicator of experience of an El Niño event, using monthly data for eight meteorological stations in Manabí (Zevallos, 2002). Six of the stations have data for both 1997-98 and 1982-83 and only one station (Boyacá) shows a significant difference in the size of the anomalies between these two El Niño events (Figure 59). The other stations display similar anomalies or even a greater anomaly in 1982-83 in the case of Chone.

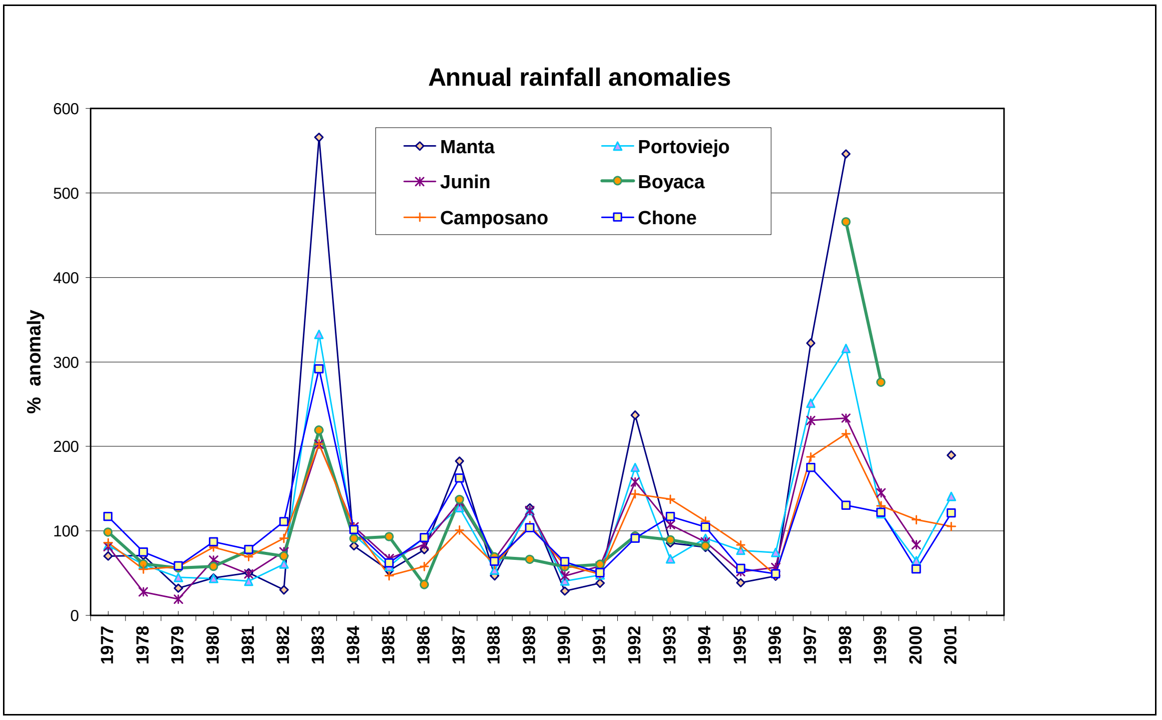

Figure 59. Precipitation anomalies for all available meteorological stations in Manabí; 1951-2001 (Zevallos, 2002)

Based on these meteorological data it is possible to select two areas that have had differing experiences of the last two strong El Niño events, Portoviejo, which received similar amounts of rainfall in the two periods and Boyacá[64], which received significantly more rainfall in the 1997-98 event (Table 47).

Table 47. Manabí counties selected according to rainfall anomalies

Historically experienced El Niño	**Portoviejo**
Less experience of El Niño	**Chone**

Selecting districts that suffered differentially in the 1997-98 El Niño event is not possible using the databases of incidents produced by the DesInventar (2004) initiative or the less comprehensive *Defensa Civil* (2002) source. Neither of these sources is referenced at the district level. Changes in poverty (see Chapter 3) also show little difference between districts within the counties of Chone or Portoviejo.

[64] The meteorological station is located in the district of Boyacá, which is within the county of Chone

Given this inability to differentiate districts according to degree of impact within the county of Portoviejo, and with the help of local experts I decided to make the sampling frame better reflect potential exposure to floods and landslides within each district. This entailed selecting areas on floodplains as well as more dissected upper catchments, in addition rural and urban areas were considered in the county of Portoviejo.

Four areas were chosen for the survey (Figure 60):

Chone county[65]

- Boyacá – the district of Boyacá and part of the district of San Antonio, within catchment of river Capricho and river Rancho Viejo (a tributary of the river Chone), rural area, 1997-98 El Niño stronger than 1982-83
- Tarugo, in Canuto and part of Chone district, catchment of rivers Tarugo and Chone, this is a rural area, close to city of Chone, 1997-98 El Niño similar to 1982-83 event

Portoviejo county[66]

- Rio Chico – the districts of Alhajuela and Abdon Calderon, in the catchment of the River Chico (major tributary of river Portoviejo) rural area, 1997-98 El Niño similar to 1982-83 event
- Rio Portoviejo – the city of Portoviejo and town of Picoazá within the catchment of the river Portoviejo, urban area, 1997-98 El Niño similar to 1982-83 event

[65] Chone is the name of a major river, and gives its name to the biggest city in northern Manabí, as well as a district and county

[66] Portoviejo is the name of a major river, the capital of Manabí province, a district and a county

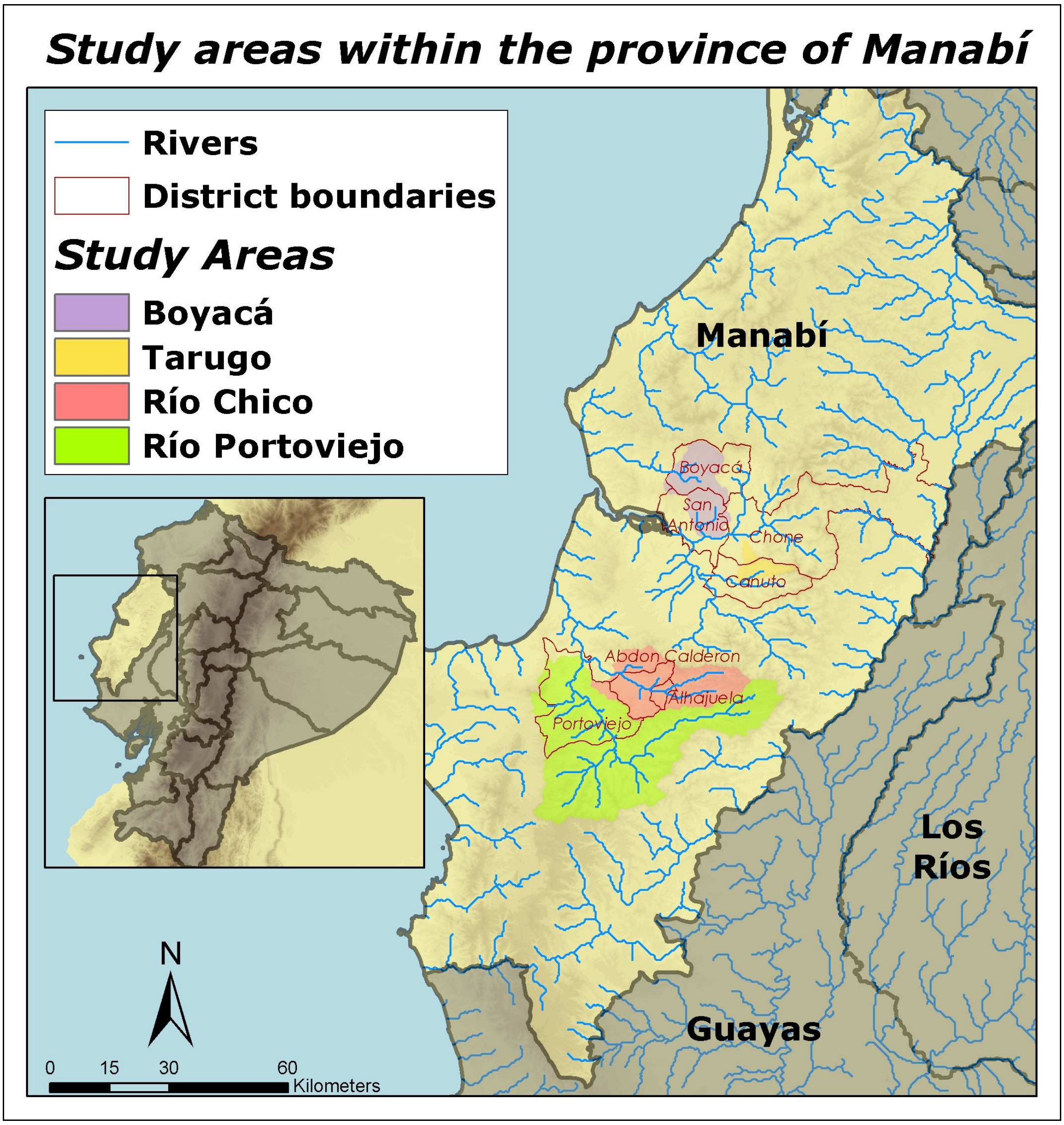

Figure 60. Areas selected for case study in Manabí province

6.2.2 Household survey

6.2.2.1 Sampling frame

The sampling frame is not intended to give a representative sample for each district rather the responses are intended to provide information that can be used to further refine a model linking assets, well-being and vulnerability to floods and landslides. Households were surveyed in eight different districts within the two counties of Portoviejo and Chone, with 106 households surveyed in each county (Table 48).

Table 48. Number of households surveyed per district

Study Area	County	District	Number of households
Boyacá - Less experience of El Niño	Chone	Boyacá	41
		San Antonio	8
		Eloy Alfaro	1
Tarugo - Historically experienced El Niño	Chone	Chone	11
		Canuto	45
Río Portoviejo - Historically experienced El Niño	Portoviejo	Picoazá	15
		Portoviejo	23
Río Chico - Historically experienced El Niño	Portoviejo	Abdón Calderon	53
		Alhajuela	15

The choice of households was made using systematic sampling. In rural areas households were selected every kilometre, while in urban areas or in the built-up parts of villages households were selected systematically (every 10th household) according to a randomly chosen direction. The rationale for this system is based on the need to capture the spatial variation in the effects of the flooding and landslides associated with the 1997-98 El Niño event. Micro and macro catchments have been distinguished and households at different locations within the catchments were selected in order to assess the impact of flooding and landslides at different points within catchments (Figure 61).

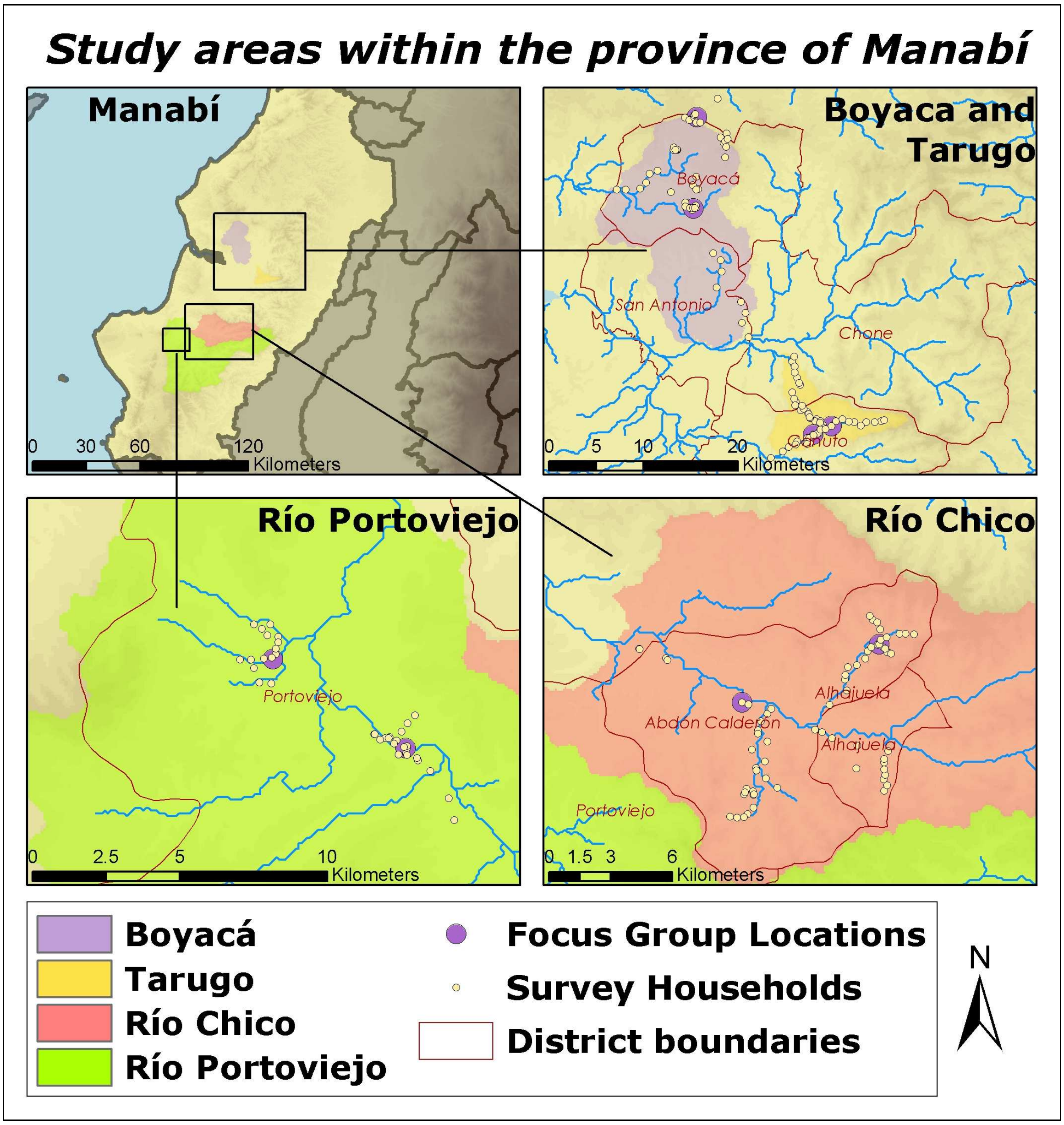

Figure 61. Location of focus group and household surveys within the areas selected in Manabí

6.2.2.2 Recall period of the last El Niño event

In this study I rely on the respondents to remember with some clarity the events of six years previous and respondent recall may be a problem. Research on respondent recall is scarce and has been limited to experiments of behaviour and social events where differences between observed and recalled attendances at events have shown up to 60% divergence. Freeman et al. (1987) suggest that two types of respondents can be discerned, those whose recall enables the long-term patterns to be revealed, and others who are able to recall with accuracy specific events.

In the case of Honduras and the 1998 Hurricane Mitch many respondents remembered clearly the event itself especially when they suffered injuries or when a family member had been killed (Rubiano, personal Communication, 2004). In general the sample of the population found it difficult to compare situations before and after the hurricane, but were able to recall specific events.

One difference between Hurricane Mitch and El Niño is the length of the event itself. Mitch was a relatively short event (1 week) of great intensity whilst the El Niño of 1997/98 lasted almost a year. This may make the recall of the totality of the El Niño event difficult if there were no specific incidents within that period, or it may be more difficult to define when exactly the event started and finished.

This factor will also have to be resolved in the field, key informants might be those who are able to recall specific events and place these events in an historical context – a mix of Freeman et al.'s (1987) good and bad respondent.

6.2.2.3 Migration of people most affected by the last El Niño

Another issue associated with the 6 year period between the validation study and the last El Niño event is that a proportion of the population may have migrated. This reduces the number of people within the study area who experienced the 1997-98 event and migration may have been more prevalent in some well-being categories than others. Additionally bias could be introduced in the responses if the interviewees were living in another region at the time of the last El Niño event[67].

Ecuador has seen vast numbers of its population emigrate to Europe and the USA although the majority of these migrants have been from the Andean region (Jokisch and Pribilsky, 2002). Total migration from the province of Manabí numbered 16,174 in the period 1990-2001 out of a population of 1.2 millions, where 3,712 migrants were from rural areas (Instituto Nacional de Estadística y Censos, 2003). The biggest increase in migrants was between 1998 and 1999 which coincides with a

[67] This second source of bias is less likely given that the region is generally a migrant provider rather than receiver.

strengthening in both push and pull factors[68]. Internal migration, both within the province of Manabí and from Manabí to the cities of Guayaquil or Quito is more difficult to assess. The 2001 population census offers only limited insights but it is possible to discern the households that have lived in their current location for less then five years. For most of the counties in the province of Manabí between 94 and 98 % of the population are long-term residents. Out migration is more difficult to identify but it is possible to see how many are still in the same county as 5 years before. The counties with the greatest proportion of out-migrants were found in the south of Manabí and which were relatively badly affected by El Niño. The out-migration rates of 14% and 9%, for Chone and Portoviejo counties respectively, are unlikely to affect the results of the survey given that migration in Ecuador is most commonly by single members of a household rather than a whole household. Data at the district level are not available, nor is it possible to assess the well-being status of the emigrants. In order to assess the impact of migration a set of questions will be included in the questionnaire instrument and in the focus groups that directly addresses the issue.

6.2.2.4 Survey instrument

The instrument used in this study was a structured interview with a mix of closed and open questions and the theme of the survey was "The impacts of the 1997-98 El Niño phenomenon on food security". The title of the survey reflects the International Center for Tropical Agriculture (CIAT) project which provided the funding for the data collection exercise. The questions in the survey were grouped around the following topics:

(1) Community and household characteristics
- Social capital resources
- Physical capital resources

(2) Assets and livelihoods
- Can the household identify their most important asset in maintaining their well-being?
- Human capital resources (education and health status)

[68] Such as the El Niño event, collapse of the financial sector, and favourable immigration policies in USA and Europe)

(3) Migration

- Magnitude and both positive and negative impacts of migration of household members

(4) Natural hazards

- Perceptions of natural hazards
- Past events

(5) The 1997-98 El Niño event

- Exposure to flooding and landslides and direct impacts
- Impacts on employment
- Impacts on food security
- Impacts on health
- Humanitarian assistance
- Long-term impact on household well-being
- Mitigation and preparedness
- Impacts on the quality of services
- Impacts on land tenure and land use

Questionnaires were pre-tested by a team of 4 experienced local enumerators and the instrument modified to remove duplicate questions and improve the clarity of the questions (see Appendix 9 for the full questionnaire). The survey was administered by the enumerators (with one enumerator replaced) and a team supervisor, seconded from the *Universidad Técnica de Manabí* (UTM) in Portoviejo, one of the CIAT project partners.

A total of 212 households were interviewed during a 2 week period between 22nd January 2004 and 6th February 2004. Household heads were requested for the interview although it was found that many were away from the homestead, either at work or due to seasonal migration in the banana plantations of southern Ecuador or the cut-flower industry of the northern Andean region. As a result many of the respondents were women or the elderly. The author did not accompany the enumerators so as not to induce response bias in the survey results.

The hypotheses which I am exploring with this survey are the following:

Hypothesis 1- Different assets within the sustainable livelihoods framework are more important than others for their influence on household well-being

This question will be asked directly to respondents, with two asset variables from each of the five asset groups[69] described in the questionnaire. Respondents will be asked to rank each of the ten asset variables on a scale of 1 to 10 (where 1 is the most important and 10 the least important variable). These scores will then be compared between households based on rural/urban location, and wealth classes.

There are also two open questions that seek to ascertain the relative importance of the different capitals available to a household in the context of the location: What is the best thing about the place where the respondent lives, and What is the least agreeable thing about the place. For these questions I code the answers according to whether the respondent refers to physical, human, social, financial or natural capital. I give each capital a value of 1 if it is mentioned, and 0 otherwise. If an asset is not mentioned as one of the best things about the place this may indicate an absence of the asset or a sufficient amount whereas for the negative aspects of the community a response may also indicate a lack or deficiency of a particular asset. Each of the questions are coded separately but have been summed to create a new variable to show the overall importance of the asset group.

A third question deals with the damages to household assets due to the 1997-98 El Niño and other natural hazards. Respondents are asked which is the most memorable natural event and to give the reasons why the event was memorable. These answers are analysed according to which assets affected during natural events are mentioned. A value of 1 is assigned when a particular asset is mentioned.

Analysing this variable is complex in those cases where a respondent mentions the same event and the same type of impact as different responses, for instance that floods affected crops and that landslides affected animals – both are impacts to the natural capital attributable to an El Niño event. I treat this as two events that happen to be classed the same and have the same impact.

[69] Asset groups are: human capital, natural capital, physical capital, financial capital and social capital.

Hypothesis 2 - The long-term impact of the 1997-98 El Niño event will be worse for those households or communities that have few assets

Different aspects of the impact will be explored – household well-being, transport infrastructure, access to utilities and health services, and changes in land tenure and land use. In addition the direct and indirect damages to the household as a result of the 1997-98 El Niño will be captured. To provide a framework for exploring this hypothesis I refer to my original definition of vulnerability:

> *An object of analysis is vulnerable when it is capable of receiving damage or loss due to exposure to a hazard. The degree of vulnerability depends on the combination of the probability of exposure to a hazard, the susceptibility of the object to suffer damage or loss, and the consequences of any damage to the long-term function of the object.*

Three important factors in this definition are the exposure to a hazard, the susceptibility of the household to suffer damages and the consequences of those damages on the livelihood of the household in the longer term. It follows therefore that these factors need to be considered in my analysis of this hypothesis. Exposure to hazards is captured at the community level but households are asked about the damages, if any, which accompanied the floods and landslides. These damages affect four of the five asset groups: physical capital, financial capital, human capital and natural capital[70]. The questionnaire has been designed to measure the medium-term effects of damages or losses by examining some of the more extreme coping mechanisms employed by households, in this case the migration of household members and the sale of land.

The consequences of both the actual damages and losses suffered, as well as the coping mechanisms employed requires information on the actual changes in well-being before and after the 1997-98 El Niño event. This longitudinal information will

[70] Social capital is not considered to be affected immediately by the floods or landslides

not be available from this survey; instead the questionnaire will capture the perceptions of the respondents with regard to the impact that the event had on their well-being.

The other important aspect of this hypothesis is the differentiation between households of their assets. Following the models developed in Chapter 2 the information from the survey provides information on assets for the different capital groups which are used to create household wealth typologies based on cluster analysis.

Hypothesis 3 - The impact of the 1997-98 El Niño event will be worse for those households or communities that have little experience of previous heavy rainfall events.

Households will be asked about all types of environmental hazards that they have experienced in the location, and which of these they perceive to have been most important. These answers will then be cross-referenced with the responses about the short and long term impacts of the 1997-98 El Niño event. Each location is classified according to the study area, which have differing experiences of previous heavy rainfall events (Figure 59).

Validation of flood and landslide models

The position of each household or interview location in the survey has been recorded with a Global Positioning System (GPS) receiver. This means that the responses of interviewees can be mapped onto the flood and landslide models as developed in Chapter 4. Questions on the exposure to floods and landslides (as well as other hazards) are included in the survey.

6.2.3 Key informant interviews

A number of key informants are interviewed at the same time as the household surveys were being conducted. The purpose of these interviews is to assess the impact of the previous El Niño event in certain locations. Informants are only questioned in the Tarugo study areas. In the other locations there were fewer opportunities for key informant interviews. No strict criteria are applied, but respondents are sought who had credibility in the community and who had experienced the 1997-98 El Niño event as well as previous events. The interviews are less structured than the household survey and give the opportunity for respondents to talk about the 1997-98 event in a holistic manner.

The method of analysis is based on the identification of key phrases, and concepts from the interviews to support the formulation of topics to be discussed in the focus group discussions. Summaries of the interviews can be seen in Appendix 10.

6.2.4 Focus group discussions

It is important to ensure a good range of experiences in the focus group discussions but I also need to take into account the dynamic of the group and make sure that all of the participants can take part without inhibitions. In the Manabí context, and indeed throughout most of Ecuador, gender relations and the concept of machismo are thought to be entrenched (Wagner, 2004; Hererra, 2001; Espinosa and Garrett, 1987) and previous experiences (Mera, personal communication, 2001,) have shown that single-sex groups often allow for more diverse responses. As a result the focus groups will be split according to sex, with women separated from men. In addition questions are modified according to the rural or urban setting of the focus group (Table 49), with questions in rural areas focussed on questions of agriculture and markets, while in urban areas there is an emphasis on human and physical capital.

Table 49. Themes to discuss in the focus group discussion

Location	Opening question
Urban / Rural	Various people have said that the strong rains are the same that have always fallen, but that the impacts are now more serious – do you think the same and why would that be?
Urban / Rural	Who suffered in your community as a result of the 1997-98 El Niño event, and how?
Rural	Who were the people most prejudiced during the 1997-98 El Niño event – those who were far from other neighbours, those who were in a community where they could buy and sell whatever product of the community, or those who always had access to the market?
Urban	Which is most important, the location of your houses or the resistance of your houses to tolerate the impacts of flooding or landslides?
Rural	We have seen that the households that depend on the income of agricultural workers were those that suffered most a scarcity of food during the 1997-98 El Niño event – do you think that the source of income is important in determining the vulnerability of households?
Urban	The majority of households interviewed say that the most important resource for the well-being of there is human capital – during the 1997-98 El Niño phenomenon did illnesses affect all of the population or were some households affected more than others?
Urban / Rural	If we knew that that the El Niño phenomenon would happen in the next year is there anything that the people could do to protect their houses or crops?
Urban/ Rural	Various, but not all, people suffered scarcity of food during the 1997-98 El Niño event, why do you think that some suffered while others did not?

Given the 6 years which separate the discussions from the 1997-98 El Niño event each group should comprise at least 6 household heads[71] aged at least 30 years old who have lived in the district for at least 8 years. Participants were selected by local leaders who were contacted some days before the meetings.

Nine focus group discussions were carried out in the study areas during October 2004 (Table 50). The team for running the discussions consist of the author, a rapporteur, and a facilitator from the region to animate the discussions without inhibiting the rest of the group.

Table 50. Chronogram of focus group discussions

Date	**Location**	**Description**
Wednesday October 6th 2004	Technical University of Manabí (Bahía de Caráquez site)	Pre-test
Boyacá study area		
Thursday October7th 2004	Boyacá town centre	2 focus group discussions
Friday October8th 2004	Las Cañas (Boyacá)	1 focus group discussions (women only)
Tarugo Study Area		
Saturday 9th October 2004	San Pablo Tarugo (Canuto)	2 focus group discussions
Sunday 10th October 2004	San Elias (Canuto)	2 focus group discussions
Río Chico study area		
Wednesday 13th October 2004	Cruz Alta de Miguelillo (Calderon)	1 focus group discussion (women only)
Thursday 14th October 2004	El Mate (Calderon)	2 focus group discussions
Río Portoviejo study area		
Tuesday 12th October 2004	Portoviejo (urban)	2 focus group discussions
Thursday 14th October 2004	Picoazá (Portoviejo, urban)	1 focus group discussion (mixed group)

The settings for the focus groups varied according to each location; in rural areas it was generally possible to use community spaces such as halls, whereas in the urban

[71] Or spouse where the household head is male and the focus group is for women (and vice versa)

locations offices of community based organisations were used. In two locations (El Mate and San Elias) private houses of local leaders (which were often used as meeting spaces) were made available.

The program for each focus group discussion was the following:

- Welcome and brief introduction from local facilitator
- Display of results of national analysis of changes in food consumption and household survey by investigator
- Discussion, using key questions led by investigator and moderated by facilitator
- Questions for investigators

The data collected were summaries of the discussions, with exact transcripts where possible (often more than one person was speaking at a time or there was noise from the environment). The method of data analysis was the categorisation of the summaries (cf. Tapsell et al., 2002; Moore, 2004) into themes based on the repetition of perceptions, ideas or concepts (Ryan and Bernard, 2000; 2003), and a discussion of the differences and similarities between groups (in the same location) and between locations. There follows a triangulation of the results of the three data sources: household survey, key informant interviews, and focus group discussions.

6.3 Results

6.3.1 Household survey

Three hypotheses are tested using the results from the household questionnaire, and the flood and landslide models compared with the responses of interviewees. Following the analysis of assets and consumption in Chapter 2 sub-groups have been created based on whether respondents considered the location of their household to be urban or rural[72]. In addition the results are analysed according to the sex of the respondent and where appropriate three wealth clusters.

[72] Rather than the perception of the interviewer or author, although in most cases the choice of urban/rural was as expected according to the maps of the province and the sample design.

I have created 3 wealth classes using household asset variables (Table 51) as inputs in a cluster analysis. 39 households were excluded from the analysis due to missing or erroneous values for continuous variables[73]. Some of the assets captured in the household survey are based on current household conditions, rather than the assets available to the household during the 1997-98 El Niño phenomenon. Other variables, such as the educational level and literacy of the household head, are unlikely to have changed since 1998. A reduced set of variables is therefore used – eliminating those most likely to have changed in the period after 1998, or those which might represent a temporary situation (Table 51).

Table 51. Variables captured in survey used in cluster analysis of household wealth

Household Asset	**Valid for 1997/98 (Y/N)**
Human capital	
Literacy of household head or other household members	Y
Level of education of the household head or other household member	Y
Health status of the household head or average health status[74]	N
Natural capital	
Current amount of land owned/rented now and in 1997/98	Y
Access to water[75]	N
Financial capital	
Dummy variable for transfers from family members who have migrated	N
Social capital	
Time in the community	Y
Physical capital	
House construction[76]	Y
Access to electricity	N

[73] Continuous variables were: (i) Time spent in the community; and, (ii) Amount of land. In some cases responses were inconsistent for unit and amount of land – an error on the part of the enumerator
[74] New variables were created for: (a) dummy variable for any literate person in the household; (b) highest level of education in household, and; (c) the average status of health for all members of the household
[75] New variable developed because many respondents depended on water tankers - this is given the same value as going to a well to get water
[76] Where more than one type of roof, wall or floor material is mentioned the poorer quality based on local judgements is the one recorded

A two step clustering algorithm was used and three classes specified[77]. The first class, containing 51 households is a mix of urban and rural households and is typified by good quality housing. Household heads are literate and while the majority only completed primary school a number continued to secondary or even tertiary level. The second class is exclusively rural, the 74 households are predominantly landowners, where household heads are literate and have been educated to primary level. Class 3 is almost exclusively rural with mixed quality housing and an illiterate household head with no formal education. Most of these 48 households have very little or no land although the biggest landowners are also in this class.

6.3.1.1 Hypothesis 1: the importance of assets

Different assets within the sustainable livelihoods framework are more important than others for their influence on household well-being

Human capital and especially the health of family members, is valued very highly as an asset. Comparing the means of the asset variables between rural and urban areas shows little difference (Table 52), with only natural and social capital displaying significant differences[78]. Specifically the importance of animals, while low in both areas is significantly lower in urban areas, while a crime-free environment is more appreciated in urban areas. It is surprising how natural capital variables are not ranked highly in rural areas. This may be because of the options that were presented to respondents which stressed the acquisition and improvement of additional land or livestock rather than the quality or maintenance of existing land and livestock. The differences between male and female respondents are also not great, with the only significant difference for social capital assets, which women granted more importance. When the wealth clusters are compared there is a significant difference in the means of the natural and social capital asset groups. Households in Cluster 1 give more importance to education than the other wealth classes but give less importance to natural capital; households in Cluster 3 gave social capital assets lower ranks. These differences essentially reflect the predominantly urban character of

[77] Using SPSS v.12
[78] At the 95% level using ANOVA

cluster 1 and the poor rural households in cluster 3 – with cluster 2 generally somewhere in between.

Table 52. Comparison of mean rank scores for asset variables, summarised by groups of households (direct question)

Asset variable	**Total**		**Urban**		**Rural**		**Female**		**Male**		**Cluster 1**		**Cluster 2**		**Cluster 3**	
	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)
Human capital																
Family health	1.58	(1.43)	1.76	(1.98)	1.55	(1.29)	1.72	(1.64)	1.41	(1.08)	1.67	(1.76)	1.49	(1.02)	1.54	(1.49)
Family education	4.43	(2.69)	3.91	(2.35)	4.56	(2.76)	4.62	(2.75)	4.18	(2.60)	3.61	(2.25)	4.67	(2.74)	4.79	(2.81) *
Natural capital																
More or better land	6.37	(2.72)	6.74	(2.78)	6.28	(2.72)	6.46	(2.70)	6.26	(2.75)	7.13	(2.52)	6.44	(2.76)	5.50	(2.78)*
More or better animals	6.88	(2.44)	7.84	(2.25)	6.65	(2.43)**	6.90	(2.55)	6.85	(2.29)	7.75	(2.33)	6.53	(2.31)	5.73	(2.53)***
Physical capital																
Basic services	4.01	(2.20)	4.39	(2.59)	3.94	(2.11)	4.26	(2.27)	3.67	(2.07)	3.91	(2.13)	3.99	(2.15)	4.50	(2.51)
Quality of housing	6.28	(2.51)	6.49	(2.48)	6.24	(2.53)	6.09	(2.68)	6.54	(2.27)	6.50	(2.31)	6.57	(2.59)	6.21	(2.29)
Financial capital																
Access to cash	6.95	(2.35)	6.99	(2.22)	6.92	(2.39)	6.98	(2.55)	6.91	(2.07)	6.90	(2.38)	7.04	(2.50)	6.69	(2.62)
Income security	5.70	(2.10)	5.53	(1.83)	5.75	(2.15)	5.89	(2.12)	5.45	(2.04)	5.29	(2.01)	6.04	(2.21)	5.73	(1.91)
Social capital																
Assistance from friends/kin	6.18	(2.23)	5.84	(2.20)	6.25	(2.25)	5.82	(2.14)	6.65	(2.27)**	6.26	(2.10)	5.72	(2.20)	6.63	(2.28)
Crime-free environment	6.58	(2.81)	5.45	(2.64)	6.82	(2.79)**	6.15	(2.80)	7.16	(2.72)**	5.91	(2.70)	6.35	(2.94)	7.69	(2.65)**

Where: 1 is the most important variable and 10 the least important

Total n=212; Urban n=37; Rural n = 173; missing = 2; Female n=120; Male n = 92; cluster 1 n = 51; cluster 2 n = 72 ; cluster 3 n = 48

Comparison of group means using ANOVA: * Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9%

Cluster 1 = rural/urban, good housing, high education level

Cluster 2 = rural, moderate education, landowners

Cluster 3 = rural, mixed housing, little formal education, little land

Table 53. Comparison of asset group importance (location characteristics)

Asset variable	**Total**		**Urban**		**Rural**		**Female**		**Male**		**Cluster 1**		**Cluster 2**		**Cluster 3**	
	Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)	
Human capital	0.42	(0.57)	0.54	(0.61)	0.40	(0.57)	0.42	(0.60)	0.42	(0.54)	0.47	(0.58)	0.39	(0.62)	0.44	(0.54)
Natural capital	0.59	(2.72)	0.30	(2.78)	0.66	(2.72)**	0.54	(0.59)	0.66	(0.65)	0.41	(0.00)	0.65	(0.00)	0.69	(0.00)*
Physical capital	0.93	(0.68)	1.08	(0.55)	0.89	(0.70)	0.88	(0.70)	1.00	(0.65)	1.06	(0.61)	1.00	(0.69)	0.69	(0.59)**
Financial capital	0.25	(0.45)	0.03	(0.16)	0.29	(0.47)**	0.23	(0.42)	0.28	(0.48)	0.10	(0.30)	0.28	(0.45)	0.35	(0.53)*
Social capital	0.55	(0.64)	0.81	(0.70)	0.50	(0.62)**	0.63	(0.69)	0.46	(0.56)	0.67	(0.65)	0.50	(0.65)	0.48	(0.62)

The minimum value is 0 and implies that the asset group is not mentioned by any household as either the most agreeable or least agreeable aspect of the community; in contrast a value of 2 implies that the asset group was mentioned by all households as a response to both questions

Total n=212; Urban n=37; Rural n = 173; missing = 2; Female n=120; Male n = 92; cluster 1 n = 51; cluster 2 n = 72 ; cluster 3 n = 48

Comparison of group means using ANOVA: * Significant at the 95% level; ** significant at the 99% level

Cluster 1 = rural/urban, good housing, high education level

Cluster 2 = rural, moderate education, landowners

Cluster 3 = rural, mixed housing, little formal education, little land

Table 54. Comparison of asset group importance (memorable event)

Asset variable	Total		Urban		Rural		Female		Male		Cluster 1		Cluster 2		Cluster 3	
	Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)		Mean (SD)	
Human capital	0.07	(0.25)	0.11	(0.32)	0.06	(0.24)	0.07	(0.25)	0.07	(0.25)	0.08	(0.27)	0.07	(0.26)	0.04	(0.20)
Natural capital	0.47	(0.50)	0.19	(0.40)	0.53	(0.50)***	0.45	(0.50)	0.50	(0.50)	0.30	(0.46)	0.46	(0.50)	0.51	(0.51)
Physical capital	0.41	(0.49)	0.67	(0.48)	0.36	(0.48)**	0.44	(0.50)	0.38	(0.49)	0.50	(0.51)	0.34	(0.48)	0.38	(0.49)
Financial capital	0.04	(0.19)	0.11	(0.32)	0.02	(0.13)**	0.03	(0.18)	0.04	(0.21)	0.02	(0.14)	0.03	(0.17)	0.02	(0.15)
Social capital	0.03	(0.17)	0.03	(0.17)	0.03	(0.17)	0.03	(0.16)	0.03	(0.18)	0.04	(0.20)	0.03	(0.17)	0.02	(0.15)

The minimum value is 0 and implies that the asset group is not mentioned by any household as being affected by the most memorable natural event; in contrast a value of 1 implies that the asset group was mentioned by all households as being affected by the most memorable natural event

Total n=209; Urban n=36; Rural n = 171; missing = 5; Female n=119; Male n = 90; cluster 1 n = 50; cluster 2 n = 71 ; cluster 3 n = 47

Comparison of group means using ANOVA: * Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9%

Cluster 1 = rural/urban, good housing, high education level

Cluster 2 = rural, moderate education, landowners

Cluster 3 = rural, mixed housing, little formal education, little land

When asked about the best and worse aspects of the place where respondents lived, physical capital is mentioned more than the other asset groups, with financial and human capitals the least often mentioned (Table 53). There were no significant differences between the responses by women or men; in contrast the responses from people in urban areas differed to those in rural areas. The magnitude of the differences in means was significant at the 99% level for natural, financial and social capitals. When the wealth clusters are considered the mean values for the financial and natural capital groups are still significantly different but instead of social the physical capital asset group show significant differences. These suggest that the urban and more educated rural households value financial and natural capital less than poorer rural households – due potentially to the differences in livelihood strategies they pursue.

The final question used to explore hypothesis 1 asks respondents which is the most memorable natural event and why. For this event the most common asset mentioned, and thus the highest aggregate score, is physical capital amongst respondents in urban areas and in wealth class 1, and natural capital for all other groups (Table 54). The differences between urban and rural respondents for natural, physical and financial capitals are all significant at the 99% level. There were no significant differences between female and male respondents or between households in the different wealth clusters.

The results of the analysis of the three questions shows that while respondents recognised the importance of human capital for their well-being these kinds of assets are not important characteristics of the community and are generally less affected by natural events than natural and physical capitals. It also seems clear that different kinds of asset are indeed considered more or less important for household well-being and that for different livelihood strategies (for instance between urban and rural residents) the importance of a particular asset group will be more or less important.

6.3.1.2 Hypothesis 2: assets to mitigate effects of El Niño

The long-term impact of the 1997-98 El Niño event will be worse for those households or communities that have few assets.

Questions were asked about the immediate impacts of the El Niño phenomenon on the physical structure of the household or crops, on the loss of employment, on the scarcity of food and on the health of the household members. Questions were also asked about the long term impacts of the El Niño phenomenon on the well-being of the household, and the cultivation of the land as well as community characteristics such as the road infrastructure, provision of drinking water, electricity, sewerage, telephone and health services.

There is no significant difference in the perceptions of respondents in the different wealth classes, although more households in cluster 1 (urban/rural) considered that their current situation had improved while rural households tended to think that their well-being had deteriorated slightly. The reason for these changes however, when mentioned, was not normally related to the El Niño event of 1997-98, instead economic woes, often associated with dollarisation in 2000, were more often quoted as the cause of changes in well-being.

When the change in land use was considered the mean value for wealth class 2 was negative, showing that households had lost land, while the mean value for wealth classes 1 and 3 was positive. The difference in means was not, however, significant. Similarly for households where members had migrated there were no differences between the clusters. When community characteristics were analysed there were no significant differences between the groups in the change in the quality of any of the services.

The reasons why different households suffered also depends upon the extent to which they were affected by the short–term impacts of the 1997-98 El Niño phenomenon. This is addressed by questions which ask the respondent if the household suffered from landslides or floods during the 1997-98 event, and if so what were the effects. When these results are cross-tabulated with the long-term impacts there was little consistent association between households that suffered damages during the 1997-98 El Niño event and the judgments of whether the household was now better or worse-off (Table 55). For flood events only the loss of animals has a significant positive association with the deterioration of well-being, whereas for households that experienced landslides there is a positive association with the loss of crops in the field or after harvest, the loss of animals and damages in general. When landslides and floods are considered together then it can be seen that the death of a family member or friend, the total loss of buildings, and the loss of crops in the field are all significantly associated at the 90% confidence level with perceptions of reductions in well-being.

Table 55. Summary of χ^2 tests on the associations between changes in well-being and impacts of 1997-98 El Niño event

Immediate impacts of 1997-98 El Niño event	**Due to floods**		**Due to landslides**		**Total**	
	χ^2	**P value**	χ^2	**P value**	χ^2	**P value**
Death of a member of family or friend	4.79	0.09	2.49	0.29	6.15	0.05
Damages to the house or other buildings	0.84	0.66	3.54	0.17	4.03	0.13
Total loss of house or other building	1.46	0.48	3.50	0.17	5.32	0.07
Loss of crops due to damage in the field	2.76	0.25	9.03	0.01	8.82	0.01
Post-harvest damage due to lack of access to markets	0.33	0.85	5.91	0.05	3.70	0.16
Loss of animals	6.16	0.05	14.96	<0.01	13.62	<0.01
Other damages	0.87	0.65	3.73	0.16	2.90	0.24
All/any damages[79]	3.23	0.20	15.38	<0.01	22.74	<0.01

Contingency tables shown in Appendix 11

[79] The response in the questionnaire is for "No damages" but the association between households that suffered "no damages" and their perceptions of longer term deterioration in household well-being was generally negative – thus the response is changed in the table to "All/any damages"

If the analysis is restricted to those households that suffered physical damage the relationship between assets and medium term impacts (selling land or migration) is still not significant. So while there are significant associations between short-term impacts with changes in well-being there is not a similar link with the medium term or secondary impacts that might have been responsible for changes in well-being.

Another complicating factor in the analysis of changes in well-being is the influence of external assistance and aid. Respondents were asked if they received assistance from friends and family as well as government or non-governmental organisations. Of the 212 households interviewed 91 received some kind of assistance. Of these the majority received aid from one source only, with assistance from the family the most common source, followed by friends, the national government, non-governmental organisations and, least frequently, local organisations.

There are two important themes concerning aid and assistance – firstly the circumstances that led to households receiving assistance, and secondly the effect that this aid had on the well-being of the household. These issues were not explored in depth in the questionnaire, but it could be assumed that families most at need would be those who received most aid. Obviously this is not always the case and there will have been other households that received assistance based on their location, i.e. the ease with which assistance could be offered. An analysis of the responses suggests that location is indeed associated with the kind of assistance available – significantly more households in the county of Portoviejo (which includes the districts of Abdon Calderon, Alajuela and Portoviejo) received help from the state and NGOs than households in Chone county (in the districts of Canuto, Boyacá, San Antonio and Chone). Households in the valley of the Río Chico (the districts of Abdon Calderon and Alhajuela) also received more help from family members than the other areas, while households in the district of Portoviejo received significantly more help from friends than households in the other locations. The corollary to this is that there were significantly more households in Chone that received no assistance from any source than in the county of Portoviejo. Only some of these differences (those relating to assistance from friends) are due to the urban or rural locations of the households, although in general rural households received less help than urban households.

Apart from the location other potential reasons for assistance include the severity of the damages which resulted from exposure to floods and landslides. Perhaps not surprisingly the assistance from the state displays no association with these very specific damages. Help from relatives, however, is significantly greater for those households that suffered damages to the house from floods, and the total destruction of buildings due to landslides, but not for other damages (such as to crops). Similarly the aid of friends is significantly higher for those that suffered damage to their houses due to floods than to households which did not suffer in this way. It seems therefore that apart from these cases the help offered was not based upon the damages caused by landslides and floods.

The effects of the disruption and damage caused by the floods and landslides were felt in the medium term as jobs and food were scarce and health was impaired. These effects might also have been a trigger for aid from outside the household. An analysis of the associations between these medium term effects shows significant associations between aid from relatives and friends to those households suffering mild shortages of food or employment, but less help to households with more severe shortages. Aid from other sources shows no significant association with these impacts. Illnesses and health problems associated with the floods and landslides had a moderately significant association with aid from families, friends and NGOs.

The effects of the assistance might be seen in differences in the need to migrate, to sell land, and ultimately in the respondent’s assessment of the changes in household well-being.
No association was found between migration and assistance from any source, but changes in land area were positively associated with assistance from governmental agencies.

There are strong associations between help given by relatives and by NGOs and perceptions of well-being. In the former case the relationship between aid and well-being was negative suggesting that help was given to relatives but that this was insufficient to have a lasting effect on well-being, while in the latter case the households that were assisted by NGOs have a more positive perception of the changes in their well-being. Meanwhile those households that received no help have in the whole experienced little change in their well-being status.

6.3.1.3 Hypothesis 3: experience and preparedness lessen effects of El Niño

The impact of the 1997-98 El Niño event will be worse for those households or communities that have little experience of previous heavy rainfall events.

This hypothesis requires an analysis of the differences in exposure between the locations, and the actual damages that were caused by floods and landslides. This is followed by an exploration of the differences in short, medium and longer term impacts. In each case the sex of the respondent, the urban and rural nature of the location and the wealth cluster will be taken into account.

Four different locations were surveyed: Tarugo, Boyacá, Rio Chico (the districts of Abdon Calderon and Alhajuela) and Rio Portoviejo (Portoviejo city and Picoazá). The choice of Boyacá as one of the survey locations was based on the meteorological data that showed the rainfall anomaly in 1997-98 to be far higher than for the 1982-82 El Niño phenomenon. Data on other events have been captured indirectly by the questionnaire and previous El Niño events or strong rains were mentioned less frequently in Boyacá than the other locations as important natural events.

The 1997-98 El Niño was by far the most important natural event in all locations, but actual exposure to hazards were different in each area. Floods were common in the Río Portoviejo floodplain, and landslides were experienced in the upper catchments of Tarugo and Boyacá, whereas a mixture of landslides and flooding occurred in the Río Chico valley which also includes the micro-catchments of tributary rivers (Table 56).

Table 56. Contingency table of natural hazards experienced by households during the 1997-9 El Niño event summarized by the group of communities

Natural hazard experienced		Group of communities: Tarugo	Boyacá	Río Chico	Río Portoviejo	Total
Floods	Experienced	8	9	14	29	60
	Expected	16.0	14.3	18.9	10.9	
Landslides	Experienced	21	29	20	0	70
	Expected	18.7	16.7	22.0	12.7	
Floods and landslides	Experienced	20	9	30	9	68
	Expected	18.1	16.2	21.4	12.3	
None	Experienced	7	3	2	0	12
	Expected	3.2	2.9	3.8	2.2	
Total		56	50	66	38	210

When the damages associated with flooding and landslides are considered it can be seen that the number of deaths was far higher in Tarugo than in the other locations, and damages to buildings were more prevalent in the valleys of the Portoviejo and Chico rivers, with Portoviejo suffering from the greatest number of houses completely destroyed. The loss of crops in the fields was particularly common in the Rio Chico location while accessibility was a bigger problem in Tarugo than in other locations. The loss of animals was more consistent among locations.

The medium term impacts – sale of land, and migration of household members – showed no significant differences between the 4 locations. The differences between the perceptions of longer term changes in well-being do show differences between the Rio Chico location and the other three areas. Households in this location felt that their well-being was worse than before the El Niño event whereas the other areas were in general more neutral in their assessment. It must be remembered however that very few households actually mentioned the 1997-98 El Niño event as a direct cause of their change in well-being.

In conclusion there is little evidence to suggest that the experience of previous events was a factor that would lessen the impacts of floods and landslides associated with the 1997-98 El Niño event.

6.3.1.4 Validation of flood and landslide models

Households were asked if their communities experienced floods or landslides during the 1997-98 El Niño event. Out of the 212 respondents only 12 considered that there had been no landslides or floods in their communities. Over half of these were in the Tarugo area but interviewees close-by recollected that their communities had indeed been exposed to these hazards. This suggests problems of recall amongst respondents or the possibility that they were influenced by the degree they were personally affected by those hazards. Of the 198 respondents who recalled hazards associated with the heavy rains of El Niño, 60 mentioned that there were floods, 70 remembered landslides in their communities and a further 68 said there were both floods and landslides.

While the locations of the interviews were recorded using a handheld GPS receiver the question asks respondents about floods or landslides in their communities. The location of floods and landslides is therefore a little fuzzy. Nevertheless it can be seen that floods are more common in flat areas close to rivers and the landslides are more common in areas with steep slopes, while a mix can be found in between. The recollections of the interviewees can therefore be used to compare with the landslide and flood models developed in Chapter 4, but are not suitable for a definitive validation.
A buffer (of 1km radius) has been created around each interview location so as to reflect the fuzzy nature of the flood or landslide occurrences. These circular polygons can then be compared to the flood (Figure 62) and landslide (Figure 63) models.

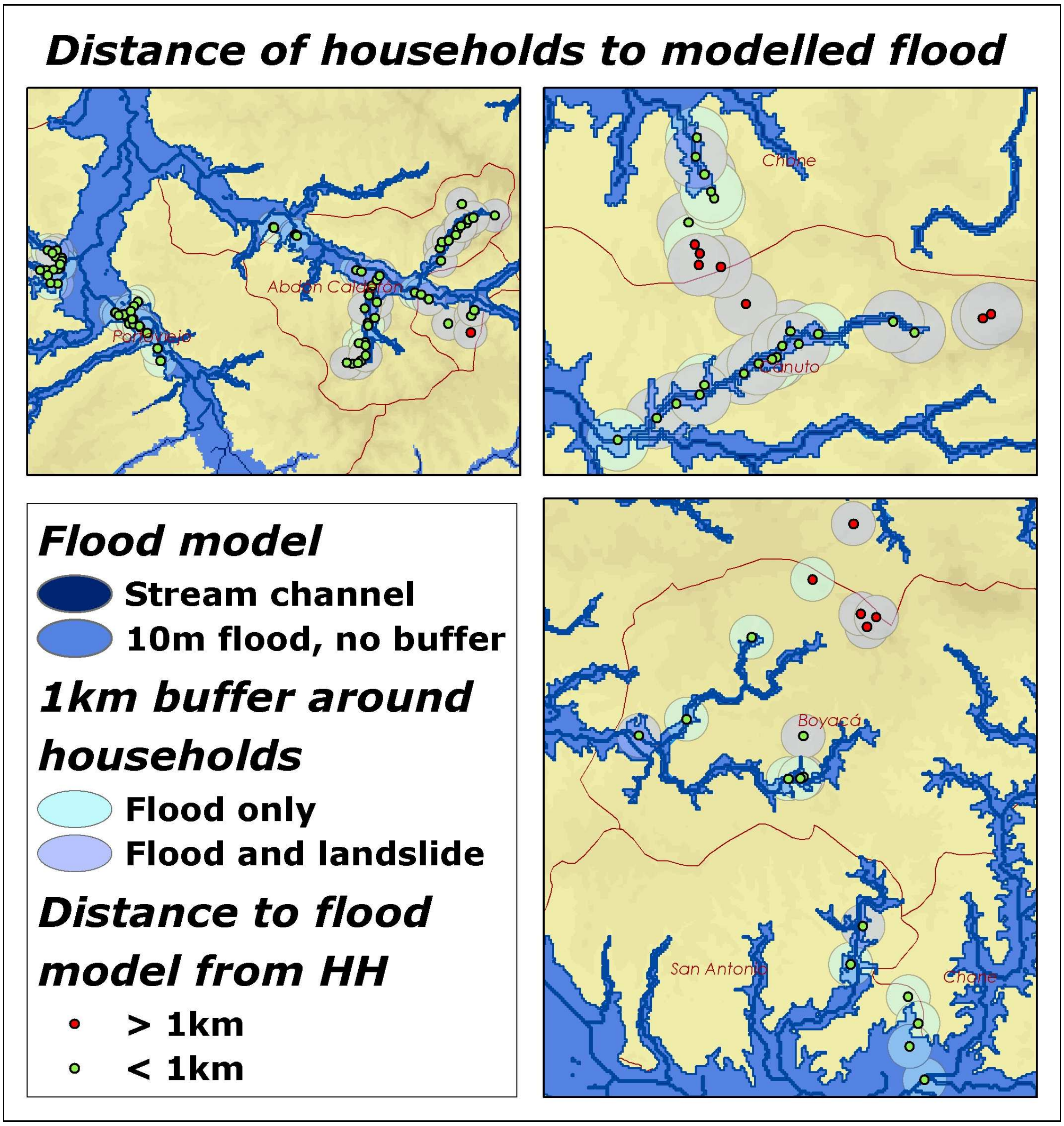

Figure 62. Households reporting occurrences of floods and distance to 10m flood model with no buffer

The flood models developed in Chapter 4 produced dramatically different results in terms of their extent. When compared to maps of the extents of previous flood events for smaller channels in upper catchments a 10m flood with no buffering was the most realistic scenario. Despite the fact that this model produced the largest area liable to flood 13 of the 127 households that recalled the occurrence of floods in their neighbourhood, are further than 1km from this modelled flood. These households tend to be close to watersheds between catchments in locations where the flow accumulation was less than 1000 grid cells (approximately equivalent to an upstream area of 8.5km^2).The number of households outside the 1km buffer increases as the flood models are made more restrictive (Table 57).

Interviewees were also asked if the floods in their vicinity had caused damages to members of their household, their crops or buildings. This question refers to the property of the respondent rather than the community; as a result I would expect that positive responses would be in areas liable to flood (rather than within a 1km buffer). Of the 116 households that reported damages only a maximum of 70% were in areas liable to flood and this number decreases markedly as the flood level (and to a lesser extent the buffer size in the flood model) is reduced (Table 57). These locations outside the areas liable to flood are not restricted to the ridges at the watersheds but are often found in valleys close to streams and many of the damages were associated with the loss of crops which might be in fields some distance from the location of the interview.

Another test of the validity of the models is to see if there are households that did not recall floods in their vicinity but which are in areas liable to flood (errors of commission), as well as households that reported floods but suffered no damages. The number of households reporting no floods but within areas liable to flooding decreases from a maximum of 34% to 0% depending on the model chosen, while the number of households reporting floods but with no damages ranges from 0-30% (although the absolute number of cases is small).

Table 57. Comparison of household survey responses to flood models

	Households reporting no floods in their vicinity n = 82				Households reporting floods in their vicinity n =128								Error
	within 1km of flood model		within the area liable to flooding		within 1km of flood model		within the area liable to flooding				*
							suffering damages n=116[80]		suffering no damages n=10		
	#	(%)	#	(%)	#	(%)	#	(%)	#	(%)	(%)
Flood level applied equally to all streams with no buffer											
10m Flood no buffer	60	72	28	34	114	90	82	71	3	30	31
5m Flood no buffer	58	70	17	20	111	87	59	51	2	20	36
2m Flood no buffer	55	66	11	13	110	87	39	34	0	0	42
Flood level applied equally to all streams and buffer distance applied according to flow accumulation											
10m flood and 20km maximum buffer	60	72	28	34	114	90	82	71	3	30	31
10m flood and 10km maximum buffer	60	72	28	34	111	87	81	70	3	30	32
10m flood and 5km maximum buffer	58	70	21	25	109	86	65	56	2	20	35
5m flood and 20km	58	70	17	20	111	87	59	51	2	20	36

[80] One respondent did not report damages but also did not explicitly say there were no damages

maximum buffer											
5m flood and 10km maximum buffer	58	70	17	20	110	87	59	51	2	20	36
5m flood and 5km maximum buffer	56	67	16	19	109	86	50	43	0	0	39
2m flood and 20km maximum buffer	55	66	11	13	110	87	39	34	0	0	42
2m flood and 10km maximum buffer	55	66	11	13	110	87	39	34	0	0	42
2m flood and 5km maximum buffer	55	66	11	13	109	86	36	31	0	0	44
Flood level and buffer distance applied according to flow accumulation											
10m maximum flood and 20km maximum buffer	54	65	9	11	110	87	30	26	0	0	45
10m maximum flood and 10km maximum buffer	54	65	9	11	110	87	30	26	0	0	45
10m maximum flood and 5km maximum buffer	54	65	9	11	109	86	29	25	0	0	46
5m maximum flood and 20km maximum buffer	5	6	1	1	52	41	16	14	0	0	48
5m maximum flood and 10km maximum buffer	5	6	1	1	52	41	16	14	0	0	48

5m maximum flood and 5km maximum buffer	4	5	1	1	51	40	16	14	0	0	48
2m maximum flood and 20km maximum buffer	0	0	0	0	3	2	1	1	0	0	55
2m maximum flood and 10km maximum buffer	0	0	0	0	3	2	1	1	0	0	55
2m maximum flood and 5km maximum buffer	0	0	0	0	2	2	1	1	0	0	55

n=210 (2 missing values for whether landslides were experienced)

* error is sum of: (1): Households reporting no floods in their vicinity within the area liable to flooding (commission); (2) Households reporting floods in their vicinity within the area liable to flooding suffering no damages (commission), and; (3) Households reporting floods in their vicinity not within the area liable to flooding but suffering damages (omission) divided by total households in these classes and expressed as a percentage

The ‘best’ model would reduce the magnitude of both the errors of omission and commission but for these flood models the errors of omission are more important. This is because the flood models show areas potentially affected therefore it is possible that a particular flood event (even a severe one) would not affect all the areas; however one would expect that the location of all households damaged by floods would coincide with the most severe flood model. The errors of commission and omission are summed and the proportion is calculated with respect to the number of households (Table 57). The flood model with the lowest percentage of errors is the 10m flood with either a 20km buffer or no buffer. In contrast the flood model with the least flooded area – a 2m maximum flood with a 5km maximum buffer – has the largest errors, does not result in any flood in the four study areas and shows little relation to the actual exposure and damages experienced during the 1997-98 El Niño event. The flood model that best reflects the number of people affected (Chapter 4) at the district level was a 10m flood with a 10km maximum buffer, the error among the study households for this flood were 32% - 3rd lowest among the flood models and a further validation of the use of this model.

Of the 136 households that recalled landslides in their community, 35 of these are in areas which have low weights according to the model of landslides based on slope and soils (Figure 63). The majority of these are in the Boyacá area and in the Río Portoviejo study area the town of Picoazá; households in the former group are in areas with moderate slopes, but when the soils are considered the weight of these slopes drops to below 0.25, meanwhile those in Picoazá have soils conducive to landslides but are in a relatively flat landscape.

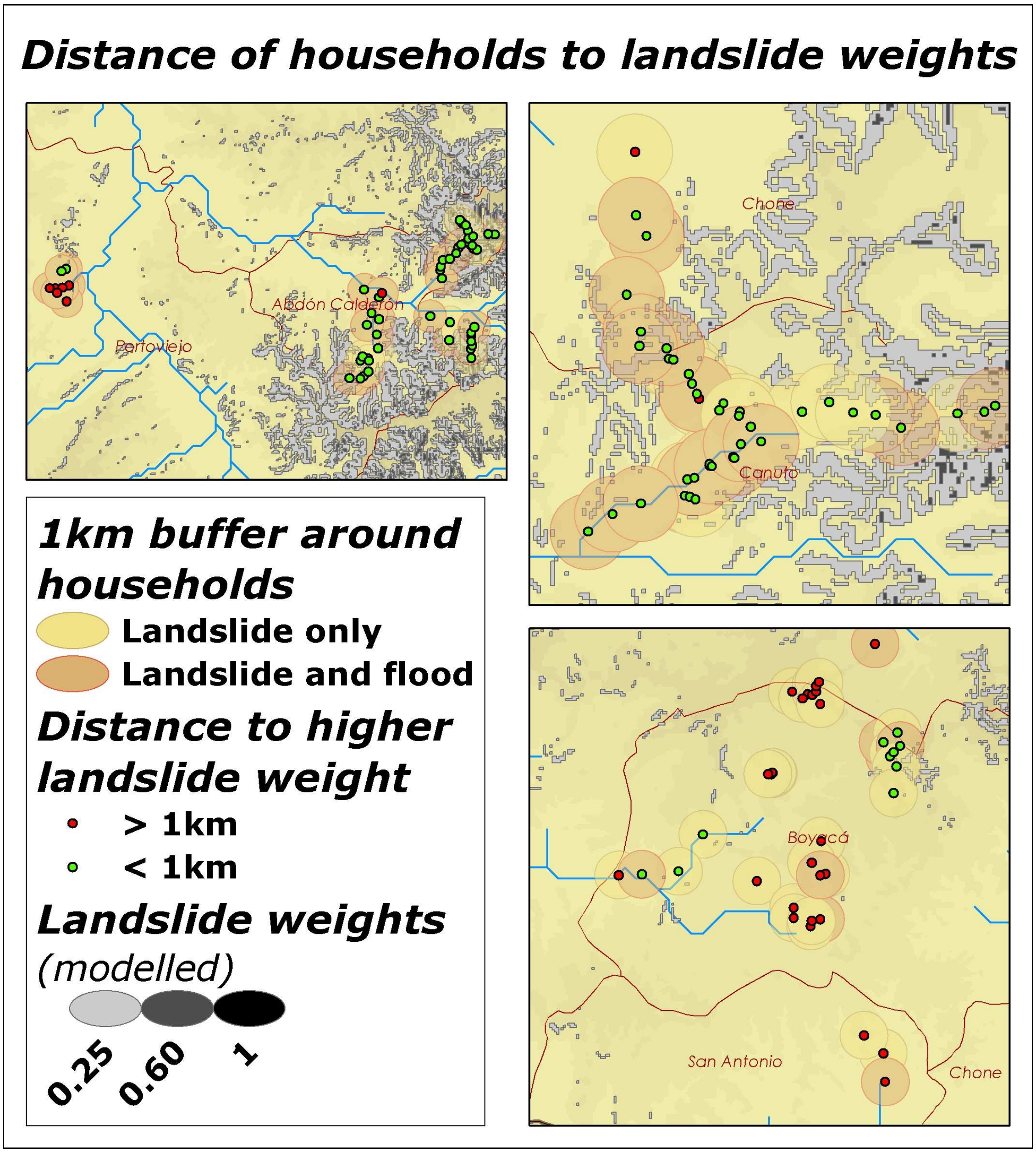

Figure 63. Households reporting occurrences of landslides and distance to higher modelled weights of landslides

Only 7 of the 138 households which suffered damages are located in areas with a higher likelihood of landslides, according to the model which takes into account slopes and soils (Table 58). The total error for this landslide model which takes into account errors of commission[81] and omission is very high at 46%. The size of the error reduces to 41% when the simpler landslide model is considered, and importantly the number of households that suffered damages due to landslides within the area modelled as susceptible to landslides increases.

Table 58. Comparison of household survey responses to flood models

	Households reporting no landslides in their vicinity n = 72				**Households reporting landslides in their vicinity n=138**						**Error**
	within 1km of a higher weight in model		**within a higher weight area**		**within 1km of higher weight in model**		**within the higher weight area**				*****
							suffering damages n=138[82]		**suffering no damages n=72**		
	#	**(%)**	**#**	**(%)**	**#**	**(%)**	**#**	**(%)**	**#**	**(%)**	**(%)**
Landslide model with slopes											
	70	97	4	6	133	96	21	15	0	0	41
Landslide model with slopes and soils											
	56	78	0	0	101	73	7	5	0	0	46

n=210 (2 missing values for whether landslides were experienced)

* error is sum of: (1): Households reporting no landslides in their vicinity within a higher weight area (commission); (2) Households reporting landslides in their vicinity within a higher weight area suffering no damages (commission), and; (3) Households reporting landslides in their vicinity not within a higher weight area but suffering damages (omission) divided by total households in these classes and expressed as a percentage

[81] There were no errors of commission for this model
[82] Two respondents did not report damages but also did not explicitly say there were no damages

6.3.2 Key informant interviews

Key themes that can be extracted from the field notes of the 8 interviews were the following:

- *Differences in experiences of 1997-98 El Niño based on actions*
- *Reduced accessibility to markets as a key impact in upstream rural areas*
- *Better accessibility opens up communities to (bad) outsiders*
- *Key events (family entombed beneath landslide) are remembered widely*
- *Local organisations exist but no mandate for environmental issues*
- *Deforestation*
- *Planning cultivation with floods in mind*
- *Protection of buildings possible in some situations*
- *Risk of looting in urban areas impedes evacuation efforts*

The interviews were in no way representative but the themes mentioned were incorporated into the focus group discussion questions and used to extract themes.

6.3.3 Focus group discussions

The summaries of the focus group discussions were grouped into themes for each of the questions that were asked:

Urban/Rural: Various people have said that the strong rains are the same that have always fallen, but that the impacts are now more serious – do you think the same and why would that be?

- *More landslides than before, perhaps due to drought before 1997-98 El Niño (EN)*
- *People cut the trees, to sell the wood, clear the land for cultivation or for fuel wood*
- *EN of 1982 considered worse by some people but majority said it was a year of two rainy-seasons whereas 1997-98 was three.*

- *The root cause of much of this is perhaps overpopulation and need to survive.*
- *In urban areas the rivers have been canalised, causing greater velocities.*

Urban/Rural: Who suffered in your community as a result of the 1997-98 El Niño event, and how?

Common Responses

- *Children suffered more due to many illnesses, they also had their education disrupted*
- *Everyone suffered equally*
- *Those who didn't have their own land (and therefore source of food) suffered in some places and had to migrate*
- *Landowners lost investments, some went into debt and had to sell their farms*
- *It was thought that traders actually benefited (if they could reach the markets and producers)*

There was some consensus that children suffered more than adults, mainly as a result of illnesses but there was less agreement that particular wealth classes suffered more than others, or it was difficult to compare the outcomes.

Rural: Who were the people most prejudiced during the 1997-98 El Niño event – those who were far from other neighbours, those who were in a community where they could buy and sell whatever product of the community, or those who always had access to the market?

- *People further from the market were worse-off because they had more difficulty travelling to buy necessities but maybe had more of their own food*
- *Those who lived further up in the hills were worse-off because they had difficulty getting down to the village*
- *Urban citizens prefer the comfort of towns and cities but need to buy everything*

All of the groups thought that people elsewhere were worse-off during the 1997-98 El Niño event. Those participants from the upper watersheds felt that they had enough of their own provisions to protect them from lack of access which was the main negative impact of the event. In the urban areas it was the lack of basic (common) services (electricity, sewerage) which was a big impact.

Urban: Which is most important, the location of your houses or the resistance of your houses to tolerate the impacts of flooding or landslides?

- *The location of the house is by far more important than the construction - sites close to rivers or riverbeds were deemed the most hazardous locations, both for flooding and for diseases and snakes*
- *In rural areas some hillsides were also thought dangerous locations*
- *Lower floors were more affected than upper floors (where buildings are occupied by multiple families) and houses made of bamboo were thought more susceptible than those made of concrete (when in the same location)*

In most locations it was the mix of mud and water that was the major impact of the 1997-98 event. There were very few cases where people were killed by landslides but they contributed to more severe and unpredictable floods. These mud-bearing floods were very dangerous to property in the short-term, killed crops and trees in the medium term and seemed to have affected soil fertility in the longer term.

Rural: We have seen that the households that depend on the income of agricultural workers were those that suffered most a scarcity of food during the 1997-98 El Niño event – do you think that the source of income is important in determining the vulnerability of households?

- *Both agricultural workers and landowners suffered equally during the 1997-98 EN*
- *Agricultural workers had no capital with which to restart*

- *Workers had more options to look for work elsewhere while the landowner had to stay*

Even though this question was directed at the rural focus groups the topic was mentioned in the urban areas. In these discussions it was mentioned that urban dwellers were often occupied in agricultural labour which suffered during the 97-98 EN and that even non-agricultural jobs were affected, such as construction.

Urban: The majority of households interviewed say that the most important resource for their well-being is human capital – during the 1997-98 El Niño phenomenon did illnesses affect all of the population or were some households affected more than others?

- *Typhoid, diarrhoea, dengue fever, malaria, cholera were the diseases mentioned as a result of the flooding and contamination*
- *Long term health effects of having to carry heavy loads (due to a lack of transportation and that pack animals could not function)*
- *Psychological problems caused by the rise and fall of rivers over a 9 month period*
- *Snakebites*

These illnesses were mentioned in both urban and rural areas. In some more remote rural areas the illnesses were not as severe. Both men and women mentioned these illnesses with children universally acknowledged as those who suffered most. Psychological problems were mentioned in the women only focus groups while the physical effects of carrying loads were mentioned in a men only focus group.

Urban/Rural: If we knew that that the El Niño phenomenon would happen in the next year is there anything that the people could do to protect their houses or crops?

- *Buy more goods (food, fuel, etc) to stock up if resources allowed*

- *More education and technical assistance required (e.g. reforestation)*
- *Growing rice is an option in EN also take advantage of early rains sowing other short-cycle crops*
- *Do nothing, just wait and see what happens and protect themselves*
- *People are poorer now (due to dollarisation) so can do nothing*
- *Clean drainage channels and dredge the main channel of the river and improve the walls*
- *Build walls around the houses*

The options for engineering types of interventions were most common in urban areas, while stocking up was a more preferred option in rural areas. In all cases it was thought that more wealthy households would be able to take these measures. There were no real differences between the responses from the men-only and women-only groups.

Urban/Rural: Various, but not all, people suffered scarcity of food during the 1997-98 El Niño event, why do you think that some suffered while others did not?

- *Those that had money were able to buy food (which had tripled in price due to transport)*
- *Some who had animals were able to eat these (but might rather have sold them but could not reach the market)*
- *Those in urban areas had less fresh produce but still some came from other parts of Ecuador which were less affected by EN*

The range of responses was similar for all groups with little discernible difference between the women/men only groups. There were some differences in the optimism of the rural groups which possibly reflected their experiences during the 1997-98 EN.

Other issues discussed:

Topics which were not part of the questions included the aid and assistance (or lack of) provided by the state or other organizations during and after the 1997-98 EN, associated with this was the perceived corruption in the planning and construction of infrastructure.

Groups in both urban and rural areas mentioned the long term impacts of lower soil fertility which was attributed to the mud which was deposited on agricultural land. Participants noted that more chemical fertilisers were now needed which had negative consequences on both their health and their budget.

Some groups compared the 1997-98 EN with previous EN of 1982-83, but more often the comparisons were made with droughts which in the rural areas were often considered worse than floods and landslides.

There was also mention in various groups, especially men-only, that there was a lack of culture of doing things oneself and looking for an easy life.

6.4 Discussion of findings

In this chapter I have shown that there are differences in the importance that households place on different assets for maintaining their well-being. These differences are also significant when households are grouped according to their location –a finding which corresponds to the models developed in Chapter 2.

Nevertheless, the importance of a particular asset group changes according to the question asked. Respondents may have difficulties in understanding and responding to a question which directly asks about the differential contribution of assets to well-being. For this reason they are asked to rank the options given, the results of which resulted in a tendency to value emotive aspects of health and the aspirational qualities of education as assets in the human capital groups. This question might have been improved with a change in the asset options, based on focus group discussions. The indirect question in contrast highlights the importance to respondents of their physical and natural capital assets which is reinforced by a question on natural hazards. There are clear differences to the responses to these questions according to scale, with human capital for instance, important at the household scale but not a characteristic associated with the community. The responses to these questions show that assets are considered differently according to scale and support the multi-level modelling approach used in Chapter 2.

The importance of different assets is discussed in the focus groups where it was felt that households which owned land and which were able to invest in agricultural production suffered differently to those households that relied instead on the sale of labour. Both households follow a particular livelihood strategy but it seemed that households dependent on the income of agricultural labourers had fewer options to cope with the disruption to production during the 1997-98 El Niño event. Households with more liquid assets such as cash or small animals were able to avoid some of the difficulties that accompanied the El Niño event by stockpiling basic goods, selling produce and actively planning for landslides and floods. It was mentioned anecdotally, however, that even ‘wealthy’ producers had been made bankrupt due to a combination of susceptible enterprises (poultry) and exposure to flood damage.

Social capital was not recognised explicitly by respondents to the household survey although it was clear that the aid of families and friends and to a lesser extent the state and NGOs was a factor in the short-term survival of numerous households. The aid and assistance appeared to be directed toward the neediest although a significant number of households that received no help at all subsequently reported deterioration in their well-being. Kinship ties appeared to be more important in the rural areas, while friendships with neighbours were more prevalent in urban areas, and despite the fact that nearly all the focal groups mentioned the unity of their communities there was little evidence of the contribution of community based organisations during the 1997-98 El Niño event.

The framework that I use to analyse vulnerability to changes in well-being follows Alwang et al. (2001) replacing ‘risk’ or a risky event with ‘exposure’ to a particular hazard, in this case to floods and landslides that were caused by heavy rainfall events during the 1997-98 El Niño event. This implies that changes in the outcome (well-being) are dependent on households actually suffering due to floods and landslides, and that the well-being outcome will depend on how the event is managed or what response the household is able to take. Numerous studies have shown that the asset base of households is a key buffer against some of the worst impacts of natural events and I have sought here to explore the hypothesis that households with fewer assets will have a relatively poorer outcome than households will more assets. This hypothesis was strengthened during the focus group discussions where it was generally felt that wealthier households (i.e. those with more assets) were able to prepare more adequately for the damages and disruption that accompanied the 1997-98 El Niño event. Assets were mobilised to mitigate the damages by reducing exposure of key assets (building walls for instance), or more commonly by stockpiling food to avoid shortages. The analysis of the structured interviews, however, is unable to provide much quantitative evidence for this hypothesis. There are a number of reasons for this. Firstly I have recognised that the changes in well-being over time which are captured by the survey are just perceptions. Secondly, it was clear that from the responses to the questions that the financial crisis, inflation and subsequent adoption of the US dollar had played a significant part in the deterioration of household well-being. Nevertheless the analysis of the questionnaire shows that there was an association between changes in well-being and exposure to damages from floods and landslide.

Another difficulty in addressing the hypothesis is that the wealth classes were created using a mix of household conditions from 2004 and 1997, with human capital assets such as education and literacy limited to the household head (which I assume are the same at the time of the survey as in 1997), while physical assets such as the housing conditions were observed directly at the time of the interview. The construction of the wealth classes using clusters was a convenient approach to reducing numerous variables and the analysis of the variables within each cluster reflects a number of plausible livelihood strategies that can be chosen. Neither these wealth classes, nor alternative indicators of wealth, were discussed in the focus group discussions.

Evidence from both the focus group sessions and the questionnaire responses do not support the hypothesis that households in the one study area (Boyacá) that had not suffered in the 1982-83 El Niño event suffered more than the other study areas. Many participants in the focus group discussions felt that the climatic event of El Niño was similar to previous events but that the effects were far worse. For many households the landslides and floods were something that previous generations had not experienced. The combination of all the responses suggest that whereas the heavy rains of El Niño had a precedent there was indeed a lack of experience of the floods and landslides, and that this unfamiliarity affected all of the study areas. This confirms the record of events in the DesInventar database (Figures 39 and 40) and implies that a reliance on the climatic data alone may not be particularly useful for determining differences in need or exposure between districts within the general area affected by El Niño.

Migration of family members was a very common experience in the households interviewed but the most common reason was due to better opportunities elsewhere rather than because the situation in the study area was particularly harsh. Wholesale migration of families away from the region due to floods or landslides was not mentioned, and in urban areas was resisted. Instead those that suffered damages to their homes received aid from family and friends where possible or simply stayed to rebuild. It is unlikely that migration, therefore, introduced bias by reducing the proportion of the population who were affected by the 1997-98 El Niño and were still resident in 2004.

Chapter 7 : Overall conclusions and discussion

The assessment of household vulnerability developed in this thesis is guided by the sustainable livelihoods framework which allows for the identification of linkages between well-being outcomes, livelihood strategies, household and community assets and the vulnerability context. Of the many strands of research that examine livelihoods I have chosen to apply and test the asset-vulnerability framework using generally available datasets for households and districts at a national scale. This allows for the replication of the approach in other geographical settings. The construction of the vulnerability assessment also requires guidance from the literature on hazards and disasters, and specifically equations of vulnerability. In this thesis I have examined each component of the vulnerability equation in detail as well as the form of the equation itself. The contribution of assets to the well-being of households, the effects at the national scale of the El Niño phenomenon, and the issues surrounding the potential exposure of assets to floods and landslides are the major themes studied in Chapters 2 to 4. These themes are combined in Chapter 5 to construct an assessment based on a vulnerability equation which is validated in a case study in Chapter 6. Each of the chapters in this thesis has concluded with a discussion of the findings which are very briefly reviewed below. This is followed by a more detailed examination of the feedback between the validation case study and the other themes, and the implications for further research.

7.1 Summary of findings

In Chapter 2 a cross-sectional econometric approach to evaluating the importance of different assets to well-being outcomes at the household level was implemented using the responses from a nation-wide household level survey. The results of multilevel regression models show that human and financial capital assets are significant correlates with well-being outcomes, but that there are differences between the urban and rural areas, and the biophysical and socio-cultural regions of Ecuador, notably for the significance of land ownership and agricultural labour.

I have shown in Chapter 3 that changes in household well-being, using summaries of household consumption and poverty levels, are associated with various indicators of the impacts of the 1997-98 El Niño event. In general those districts which were worst affected by the event were also more likely to have experienced a greater deterioration in well-being than those not affected, but the strength of the association depended on the indicators chosen for the impacts and well-being. Whilst attributing changes to the El Niño event is complicated by other contemporaneous macroeconomic shocks, these other shocks were aspatial and affected all regions (Larrea, 2004).

Exposure to hazards is a key component of vulnerability equations and one which is poorly documented in many countries. Therefore, in Chapter 4 I have described ideal models of exposure to floods and landslides, which I use to develop spatially explicit models. The combination of these models with population datasets to derive district-level simulations of the number of people potentially exposed to these hazards is a key innovation for Ecuador. Comparisons with high resolution maps of actual events as well as reported incidents of damages allow for the selection of best-fit exposure models.

The results of Chapters 2 and 4 are used in fifth chapter to produce a vulnerability assessment that incorporates the susceptibility of assets, the exposure to hazards, and the capacity to manage risks and cope with loss or damages to assets. The assessment is based on a vulnerability equation and allows the measurement of vulnerability in terms of the number and proportion of the population affected in each district. The assessment shows that for districts in the Coastal region the basins of the Guayas, Portoviejo, Chone and Esmeraldas rivers have large populations vulnerable to floods and landslides. The Andean region is in general less affected but the capital city of Quito has a large population vulnerable. Vulnerability in the Amazon region is greater in the northern districts and to a lesser extent those districts in the foothills of eastern flanks of the Andes range of mountains.

7.2 Implications for further development of vulnerability assessments

One of the objectives of this study has been to highlight the practical considerations of constructing a vulnerability assessment. This has entailed research across a broad range of disciplines that study susceptibility of assets, exposure to hazards, and capacity to cope. Arguably the greatest contribution that this thesis makes to vulnerability research is the integration of these different strands of research. The construction of the vulnerability assessment can be viewed from the perspective of the "eight steps" protocol described by Schröter et al. (2005), which was formulated to ensure consistency between vulnerability assessments in different contexts. All of these steps have been followed including, during the focus group sessions, the communication of findings to those being studied. The experiences here also follow those envisaged by Polsky et al. (2007) whereby iteration between the eight steps is likely. Indeed my research design introduced in Chapter 1 envisages that the findings from the validation case study can be used to improve subsequent assessments of vulnerability in an iterative manner (Figure 64) mixing quantitative data at the national level with more qualitative local studies.

In the remainder of this section I comment first on the implications of the findings from my case-study in Manabí province on the research undertaken in Chapters 3 and 4, and conclude with the repercussions for the research in Chapters 2 and 5.

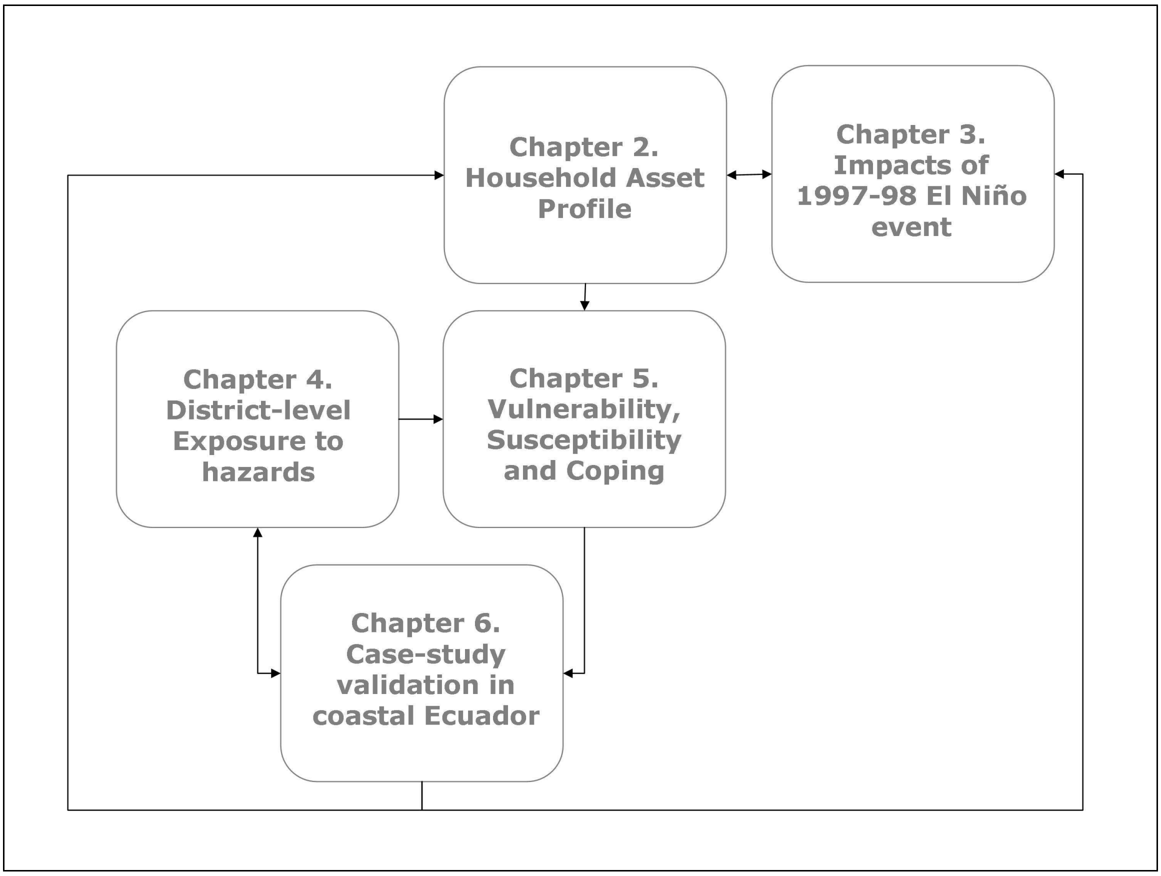

Figure 64. Research design showing main components and links between components including potential feedback loops

The analysis of the structured interviews shows that there was an association between changes in well-being and exposure to damages from floods and landslide due to the El Niño event of 1997-98. Nevertheless there are two important caveats that need to be made. Firstly I have recognised that the changes in well-being over time which are captured by the survey are just perceptions and problems in recollection were an issue in the questionnaire although less evident in the focus group sessions – possibly due to the accurate recall of some participants as well as the fact that many people were able to recount specific events. Secondly, as noted in Chapter 3, few respondents mentioned long term changes in well-being that could be directly attributable to the 1997-98 El Niño event. Instead the financial crisis (of 1999), inflation and subsequent adoption of the US dollar were thought to have played a significant part in the deterioration of household well-being. These results confirmed the findings in Chapter 3 and highlight the need for a longitudinal design for household surveys to track well-being over time. The analysis of such a survey would allow for a better understanding of the impacts on household well-being of shocks and the relationships between assets, consumption poverty and hazards (such as El Niño). This has been done in the BASIS collaborative research project which draws on longitudinal studies (Adato, Carter and May, 2006 in Moser, 2008). A compromise would be to include questions on exposure to hazards and impacts on well-being in cross-sectional household surveys (such as the LSMS used in this thesis) which are combined with qualitative studies (e.g. Tesliuc, 2003; Duflo and Udry (2001) in Foster, 2002, or to a lesser extent Hentschel and Waters, 2002).

The comparison of the flood models with the recollections of respondents suggests that the threshold used in Chapter 4 for flow accumulation of 1000 cells (an upstream area of approximately $8.5km^2$) was too large to account for all the floods experienced. The comparison between the flood model extents and the responses from the interviews are weakened because the interviewee was asked about the absence or presence of flood events in the community, rather than at the location of the interview. Nevertheless the impact of those floods can be mapped and it was shown that the flood model with the largest extents were those that best reflected the damages caused by the floods of the 1997-98 El Niño event. These results verify the findings of the comparisons between the population potentially exposed to floods in each county with those recorded in the DesInventar database.

Validation of the landslide models developed in Chapter 4 was less impressive but it has to be remembered that in contrast to the flood model the landslide model deals with more stochastic events, makes more sense at the national scale, and is best used to give relative weightings between districts. Even so, it is clear that many landslides occurred in Manabí in areas which are given little weight and this model may need to be revisited, with more evidence needed for the susceptibility of soils to landslides and more accurate and precise data sought. In concordance with the conclusions of Chapter 4 the most simple landslide model – that includes just slopes – had fewer errors in general and importantly less errors of omission.

The recollection of events from six years previous was a factor that was most evident from the response to whether the community had experienced floods or landslides, and there were numerous examples of households in the same vicinity giving conflicting replies. The vast majority of respondents that remembered landslides or floods in their vicinity also reported damages, suggesting that these experiences affected the recall of events (confirming the findings of Rubiano [personal communication, 2004] in Honduras). The importance of the recall in the case of validating the landslide and flood models is made less important because the households that suffered damages were more likely to remember them.

The feedback between the validation case study and the development of household asset profiles in Chapter 2 is also linked to the role of assets within the susceptibility and coping components of my vulnerability equation in Chapter 5.

The analysis of the importance of different capital groups from the household survey shows that households put a high value on human, physical, and natural capitals; however in applying the asset-vulnerability framework I have only considered the importance of assets in terms of their susceptibility. This has resulted in the typology of households according to the susceptibility of their assets, constructed in Chapter 5. The implications of the results of the case study are that assets are of more importance for risk management and coping. For example it was seen that some households with access to more land were able to move animals out of flooded areas, or had the resources to invest in walls to protect buildings. While the hypothesis was not tested statistically the information from the focus groups provides clues as to how assets are potentially useful to mitigate the effects of some of the secondary impacts of floods and landslides such as the loss of accessibility to markets or the increase in prices.

Instead of susceptible assets it is evident that of more importance is the susceptibility of livelihood strategies and activities, such as the sale of household labour locally or in more distant locations. Likewise a common observation was that the location of buildings and crops was a more important factor than the quality of those buildings. Pressures on land due to soil fertility decline and over-population are causing more marginal areas to be built upon or cultivated. The occupiers of these lands are often those families who have few other livelihood options. These findings suggest that livelihood strategies should be given a more prominent place in the assessment of vulnerability to El Niño in Ecuador than the household assets in isolation. Individual level data in the housing and population census would allow for the diversity of income sources, and the dependence on agriculture (e.g. Hahn et al., 2009), or ‘precarious’ urban strategies in the informal sector (Wisner, 1998, p28), to be determined at the household level, although different production strategies and reliance on remittances (e.g. Eakin and Bojórquez-Tapia, 2008) would be difficult to capture.

The capacity to cope was an important component of the vulnerability assessment in Chapter 5, with an index of unsatisfied basic needs used as a proxy for household capacity. It is mentioned in the interviews and focus groups that wealth allows households to avoid hazards, and to protect their assets, which validates the use of the basic needs index in the vulnerability assessment. The unsatisfied basic needs index also has the advantage of being available throughout Latin America and allows vulnerability to be assessed in a similar manner throughout the continent. More complex conceptions of the capacity to cope are likely to limit the potential for comparison between assessments (Polsky et al., 2007). The results of the focus group sessions showed that the types of coping strategies that were employed moved along a classical sequence of reversibility (e.g. Maxwell and Frankenburger, 1992). There were, however, differences in these stages according to whether a household owned land, with landowners resorting to selling land while non-landowners were forced to migrate confirming Corbett’s suggestion (1988) that poorer households move more rapidly along the sequence.

Due to a lack of available data community capacity to cope was not considered in the vulnerability equation; however the case study shows that assistance from outside of the household is one of the coping strategies that households might be able to draw on, especially when the aid is related to social capital assets. The source of the aid changes according to location with urban areas benefiting more from friends while rural households depend on family. Assistance from outside agencies is not received equally with significantly more recipients in some locations than others. The biggest factor precluding the incorporation of these kinds of factors in the coping component of the vulnerability equation will be the availability of datasets on social capital. A more general consideration is the effect of relief or development assistance on the relationships between assets and well-being. For instance relief aid could have improved well-being (say by direct transfers, or food aid) in the short term while diminishing assets, leaving households more vulnerable but with higher current levels of wellbeing. In addition these kinds of transfers can make it more difficult to find associations between changes in well-being over time and the impact of shocks, such as the analysis in Chapter 3.

7.3 Policy Implications

One of the main objectives of the research described in this thesis has been to provide information and analyses that can be used to improve the design of policies related to vulnerability to natural hazards. Cannon et al, (2003, pg 4) propose that vulnerability analysis "should be capable of directing development aid interventions, seeking ways to protect and enhance people's livelihoods, assist vulnerable people in their own self-protection, and support institutions in their role of disaster prevention." At the initiation of the investigation I primarily considered policy makers at the national level but it is clear that the policy environment covers a number of different and overlapping scales and with numerous actors. Hence I deal first with the implications of this thesis for policy makers in Ecuador and then more generally in developing world contexts.

Within Ecuador the principal target of the assessment was for the civil defence system which was comprised of a directorate at the national level and semi-autonomous provincial organisations. The system was eliminated in 2008 and replaced with another organisation, the "national secretary of risk management" (SNGR) (Diario Hoy, 2008). The new organisation has recognised that risk management is not a part of the daily activities of households or institutions in Ecuador and has proposed to implement a risk management communication strategy (SNGR, 2008[63]). Despite the re-organisation the emphasis of the institution is still focussed on the physical management of hazards, and short-term responses to disasters. It is therefore likely that the individual components of the vulnerability assessment – specifically the models of potential exposure to floods and landslides developed in Chapter 4 – would have the greatest utility within the institution. The case study in Manabí has confirmed the poor dissemination of this kind of information that could be used at local levels (Vargas et al., 2009). At the same time indigenous risk management mentioned by communities in Manabí in Chapter 6,

[63] http://www.snriesgos.gov.ec/index.php/iquienes-somos/informacion-institucional/politicas-y-lineas-de-trabajo-para-el-sistema.html?view=item&id=24&item=1

does not appear to be incorporated in the methods used to build capacity in risk management by the SNGR. The inclusion of these discussions and local perceptions of the root causes (such as deforestation or channel straightening) in analysis by bodies such as the national secretary of risk management would likely enhance the receptiveness of the communities to recommendations on reducing risks (International Federation of the Red Cross and Red Crescent Societies, 2009).

Community and household level risk management also allows for a broader conception of managing both the physical hazard as well as the secondary effects, more akin to self-protection (Cannon, 2008). However the case study showed a lack of community or local organisations that had an environmental or risk management remit, although there was some evidence for local institutions with social protection goals. This institutional deficiency makes participatory risk management (Tran, 2008) and people-centred early warning (International Federation of the Red Cross and Red Crescent Societies, 2009) more difficult to implement. A concrete recommendation of the study would be the formation of these organisations within Ecuador; this is a finding which is likely to be valid for other contexts.

Moving to a higher level, Patt et al. (2009, pg 3) contend that vulnerability to global change should be investigated within the domain of policy analysis, with scientists (from natural or social sciences) providing information on specific indicators within a space for dialogue. Latin American regional disaster management organisations have historically been concerned with the assessment of disasters during and shortly after events. Some organisations, such as CEPREDENAC in Central America, have started to pay greater attention to disaster prevention and discussing longer term vulnerability issues (Fagen, 2008). These agencies act in collaboration with national systems so instead of using vulnerability assessments directly it is likely that they could play an advocacy role in shaping the use of and demand for information products. This has also been proposed for other regions (e.g. African Union, 2004). The implications for those conducting vulnerability assessments are that they must engage with regional organisations on the use of assessments.

At the international level consistency between countries is necessary for comparisons that can be used as tools for targeting resources by bilateral or multilateral donors, but as with poverty there are problems when a common conception of vulnerability is used. Adger (2006) sets out the criteria for such a generalised measure of vulnerability, which draws on both development and hazards research and which incorporates the dynamic nature and depth of vulnerability, and the complexities of a socio-ecological system. However, unlike poverty metrics which can be captured using just one instrument, an assessment of vulnerability will require information on various components. The assessment presented in this thesis goes partway to produce such a generalised measure of vulnerability and the findings suggest that researchers from specific disciplines should continue to provide components of assessments. In the case of Ecuador a mixture of multilateral organisations, the national statistical agency, international NGOs (LaRed) and interested individuals made this analysis possible. The recommendation would be to publish these data but provide metadata that allow users to judge the accuracy and usefulness of a particular source. It has been shown that the unsatisfied basic needs index can be used to represent capacity to cope, this has the advantage of being collected in various Latin American countries, due in part to policies on population census instruments (Santos et al., 2010) by the Economic Commission for Latin America and the Caribbean (ECLAC).

A final policy arena relates to the strengthening of assets at the household level. Findings relevant for policy from this thesis are drawn mainly from Chapter 2 and Chapter 6 the case study in Manabí. In Chapter 2 I assessed the importance of assets but the purpose of the analysis was not to show that more assets contributed to wealth, rather which assets were most important. Nevertheless the models showed that higher levels of physical capital were positively linked to well-being but with some doubt about the causality. In contrast it was easier to show the positive contribution of human capital assets to well-being outcomes. There existed some differences between urban and rural sectors implying that policies for strengthening assets should take location and livelihoods into account – these were confirmed in the case study. Of interest were those assets that were negatively associated with well-being, such as land ownership for urban dwellers and the sale of agricultural labour in rural settings, again these have implications on policies directed towards households pursuing particular livelihood strategies. These findings do not directly relate assets to vulnerability, for this I rely on the case study, which suggests that wealthier households are better able to withstand the impacts of natural hazards. A further consideration for asset strengthening policies is the effect of hazards on the exchange value of assets and the returns (Hoddinot et al., 2005) that are possible during an event such as the El Niño phenomenon. This implies that efforts should be made to ensure accessibility to markets and sources of employment is maintained through the strengthening, maintenance and appropriate design of common assets such as roads and bridges.

7.4 Reflections on the process and lessons learned

7.4.1 Epistemological stance

The starting point of the research on vulnerability was to incorporate a dynamic element to maps and analyses of food poverty in Ecuador (Farrow et al., 2005). These maps of food poverty estimates at the district level were based on econometric analyses derived from household data. The underlying epistemological stance of the research is positivist, while the disciplinary background of the researcher is geographical information science with experience of analysing quantitative data. Previous assessments of vulnerability to natural hazards carried out by CIAT – the institution where the author is employed - were hazard specific with a strong emphasis on the modelling of potential exposure to flooding and landslides (Winograd et al., 2000). This experience and stance has inevitably been carried over to the research reported in this thesis.

Positivist approaches to assessing vulnerability have tended to concentrate on the probability of exposure to a physical hazard and to recommend interventions that reduce exposure. These approaches have had some success in contributing to the development of policies due to policy-makers' concentration on aggregate populations rather than on differences at the individual, household or community scale (Mustafa, 2002; Mustafa 2004). The same studies suggest that policy-makers at the national level tend to prefer quantitative assessments rather than an exploration of the fundamental causes of differences in vulnerability. This recognition has also contributed to the epistemological stance of this thesis and the nature of the outputs of the assessment.

The fact that my assessment draws heavily on the sustainable livelihoods framework ensures that the research incorporates most components of social vulnerability. Nevertheless there are theoretical perspectives on vulnerability, notably political economy and constructivist approaches (McLaughlin and Dietz, 2008), that are not considered in my assessment. As a result there is little deliberation of culture, social structure, and human agency which determine, amongst other things, how the households frame their well-being, and their capacity to manage risk. In my assessment I concentrate on commonly measured development outcomes to capture well-being. These consumption-poverty outcomes are consistent with political objectives such as the United Nations millennium development goals and take advantage of data that are representative at the national level. However, alternative well-being indices can be captured (Ravnborg, 1999) and these have been successfully scaled-up to the national level (Leclerc, 2010); the use of such indicators would allow for more participation from those whose vulnerability is being assessed.

Political economic issues of class relations and equality are mentioned only obliquely in my assessment and I have assumed that the value of assets as an endowment set (in their contribution to livelihood outcomes and as part of the coping strategies) is equal for all households. This overlooks a large body of evidence which has shown that households are vulnerable not just to damages to endowments but also to the entitlement exchange mapping of those endowments due to the direct or indirect effect of natural hazards (Sen, 1981). The sustainable livelihoods framework does not consider political capital, or rights as part of the asset groupings, instead they are considered separately (Figure 3). This is similar to the access model (Blaikie et al., 1994) which also has the structures of domination as a separate component, rather than as part of the formal asset set for the household. These issues were more prominent in the case study in Manabí province described in Chapter 6, where changes in the entitlement exchange mapping caused labour endowments in urban settings among semi-skilled workers to lose value. Similarly, production assets in rural areas also lost value due to damages to the physical infrastructure not of the household but of the community in the form of flooded or impassable roads. There was also some evidence for unequal access to aid and assistance although this was analysed spatially rather than from a class or wealth perspective, and an intriguing association between households whose landholdings increased and assistance from government agencies.

A number of authors have suggested the consideration of multiple units of analysis which are differentially vulnerable, in particular the impact of responses to natural hazards by households, communities and nations on the natural environment (e.g. Dow, 1992; Adger, 2006; Polsky et al., 2007; McLaughlin and Dietz, 2008). These interactions in socio-ecological systems were evident to a number of the households and communities that were interviewed in the case study. While multiple levels were addressed in Chapter 2 a full consideration of multiple units of analysis was beyond the scope of this thesis due to my use of the sustainable livelihoods framework which has been recognised as lacking links between the micro and macro scales (Moser, 2008). A further criticism of the sustainable livelihoods framework is a lack of analysis on the root causes of the impacts of hazards (Cannon et al., 2003) which implies a multi-temporal assessment of vulnerability such as the pressure-disaster-release model (Blaikie et al., 1994).

7.4.2 Practical reflections

In addition to my consideration of the epistemological stance of the research there are a number of reflections on the practical aspects of how the research was carried out from which some lessons have been learned.

One of the most important reflections was the use of three separate frameworks: the sustainable livelihoods, the asset-vulnerability, and the risk-chain approaches. This is consistent with what Polsky et al. describe as the cobbling together of methods from different traditions (2007, p 473). In this sense I made a decision to limit the depth of the analysis (to one unit of analysis) in order to take advantage of using well-known and widely used approaches. These kind of trade-offs are likely to be unavoidable especially when availability of data are taken into account. The terminology used in this assessment was also a conscious choice, with terms such as exposure, susceptibility (sensitivity), and coping capacity chosen due to their dictionary definition and widespread use within much of the literature on vulnerability to natural hazards.

The principal constraint in the research process was the time available for the capture of primary data in the province of Manabí in Ecuador. This was due to short duration of the CIAT project that provided access to secondary data for the research as well as funding for primary data capture. This time constraint implied that the fieldwork was carried out before all the components of the vulnerability assessment had been completed. The result was a sampling strategy for primary data collection that was not entirely consistent with the rest of the assessment. The sampling strategy was based on differentiation of experience of past events; however this aspect was not subsequently incorporated into the coping strategies used in the assessment.
Quite apart from the time constraints there might also be doubts about the quality of the data used as the basis for the 'experience of El Niño', i.e. the meteorological records from stations in the province of Manabí. These data were obtained from one source but were not available from the national agency responsible for measuring and managing meteorological data. The use of these anomalies as a basis for sampling was sound but the analysis of the case study showed that the meteorological event was not the only component of the hazard and that environmental degradation had contributed to cause most of the damages.

While am I able to make recommendations for vulnerability assessments based on the case study it could be argued that this should have informed the national level vulnerability assessment from the start rather than as a validation exercise. This kind of data would have been difficult to incorporate since it would require primary data capture over a larger area and it was the purpose of my study to see what can be achieved with the information already in the public domain.

The household sampling could also have been improved with better stratification of households (rather than the ex-post clustering), based on locally defined wealth classes and a list of households. The use of handheld GPS in recording the locations of interviewed households was essential for validating the exposure models that were developed in Chapter 4. This practice also allows for a sampling strategy that takes account of spatial phenomena (e.g. Kumar, 2007). While the systematic sampling of households in my case study deliberately captured households in a wide variety of landscape positions, the sampling process would have benefited from the maps of potential exposure to floods and landslides.

Another reflection of the research process concerns the time and resources spent on the different components of the vulnerability assessment. The analysis of the contribution of different assets for household well-being took a great deal of time, especially when the contribution of this component in the final vulnerability assessment was the least convincing and the most difficult to incorporate in the vulnerability assessment. The multi-level modelling did not yield large benefits over conventional multivariate analysis perhaps due to the fact that there were larger differences between households than between districts.

The creation of the models of potential exposure was necessary in Ecuador where previous models were shown to be deficient, the time required to produce these models may not be available for all researchers. A recommendation would be to have well validated models of exposure in the public domain that can be utilised in vulnerability assessments.

In general this thesis has achieved the objective of producing an assessment of vulnerability to low levels of well-being as a result of natural hazards associated with the El Niño event in Ecuador. The thesis has also shown positive associations between changes in poverty and the impacts of the 1997-98 El Niño event at the national level but recognises the difficulty of definitively attributing changes. This finding was confirmed in the case study in Manabí province and the thesis recommends longitudinal studies at the household level to clarify the impact of specific shocks on household well-being. The analysis of assets and well-being outcomes shows that human and physical capitals are more important than other asset groups but that there are differences according to rural or urban locations. These assets may be susceptible to exposure to natural hazards but the case study showed that human capital was less affected than physical or natural capital assets and that location of livelihood activities was the most important factor contributing to impacts at the household level. This finding has led to the recommendation of considering the importance of sustainable livelihood strategies in the susceptibility component of a vulnerability assessment, rather than assets alone.

The biggest constraint to producing the assessment has been the quality of the data available, but improvements have been made when compared to previous assessments, due in a great degree to the availability of some key datasets. The DesInventar database has been shown to be an invaluable resource for directing and validating the components of the vulnerability equation and efforts should be made to continue the documentation of incidents related to natural hazards like floods and landslides. Similarly the creation of specialised basic global or national datasets – like the SRTM elevation models, the derivative HydroSHEDS products, or population estimates – allow GIS practitioners to produce customised vulnerability assessments. These datasets require conceptual frameworks that draw on theories of both development – such as the sustainable livelihoods approach – and on disaster management, in order to produce assessments that are appropriate, actionable and replicable.

Appendices

Appendix 1: Variables in the 1990 population census

Individual level questionnaire

Relation of the respondent with household head
Sex of the respondent
Age of the respondent
Place of birth of the respondent (combination of district, county and provincial codes)
Current residence of the respondent (combination of district, county and provincial codes)
Where the respondent lived 5 years ago (combination of district, county and provincial codes)
Is the mother of the respondent still alive
Literacy level of the respondent
Currently attending an educational establishment
Civil status of the respondent
Educational level of the respondent
Highest grade achieved
Years of formal education
What activities were carried out in the past week
Any activity in past week even without pay
Principal occupation of the respondent
Occupation group
Occupation sub-group
Branch of activity
Group of branch
Sub-group of branch
Sector of the economy
Number of hours worked during past week
Category of occupation
Number of live births (women respondents only)
Number of children currently alive
Total number of children
Year of birth of last born child

Month of birth of last born child
Last born child still alive?
Number of homes in the population
Number of people (in home)
If the language is indigenous
Poverty level
Sociological definition of the area (city/country)
Admin. Area (urban / rural)

Household level questionnaire

Is the house used for any economic activity?
Economic activity code
Group of economic activity
Sub-group of economic activity
Is there a room used exclusively for cooking?
Type of fuel used in cooking
Condition of occupation
Number of bedrooms
Shower in the house
Electricity in the house
Sewerage system
Solid waste disposal system
Home inside the house
Language spoken
Source of water provision
Rooms in the house
Wall material
Floor material
Anybody present
Type of toilet
System of water provision
Number of people
Number of dormitories
Roof material

Telephone in the house

Tenancy of the house

Type of house

Number of households

Number of men in the household

Number of women in the household

Number of people in the household

Sociological definition of the area (city/country)

Consumption (estimated)

Poverty levels

Admin. Area (urban / rural)

If the language is indigenous

(Instituto Nacional de Estadistica y Censos, 1990)

Appendix 2: Households Surveyed in the 1995 Encuesta de Condiciones de Vida

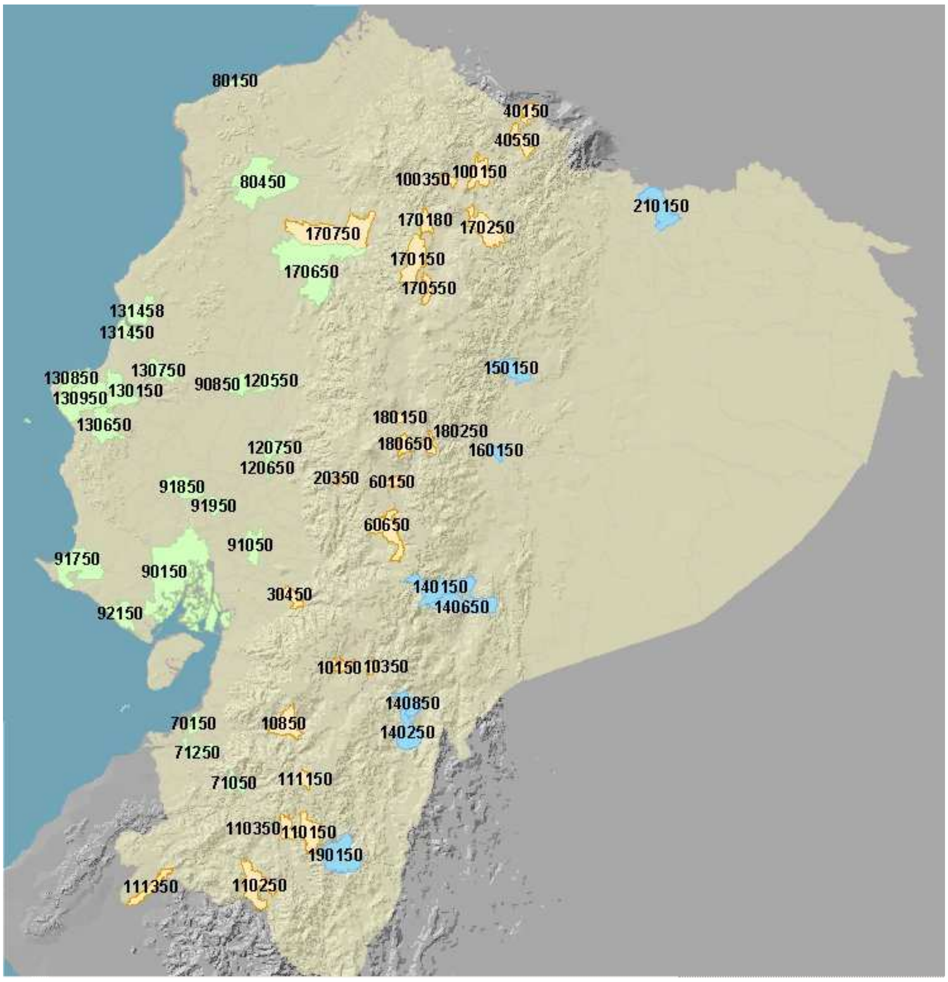

Figure 65 *Parroquias* included in the 1994/95 *Encuesta de Condiciones de Vida*
Green = Coast, Orange = Andes, Blue = Amazon

Table 59. Household type per *parroquia* included in the 1994/95 *Encuesta de Condiciones de Vida*

Domain	Region	Parroquia	Code	Urban Area	Periphery	Rural Clustered	Rural Dispersed	Total
1	1	Quito	170150	756	21	37	161	975
1	1	San Miguel De Los	170750			24	48	72

		Bancos						
				756	**21**	**61**	**209**	**1047**

Domain	Region	Parroquia	Code	Urban Area	Periphery	Rural Clustered	Rural Dispersed	Total
2	2	Chongon/Guayaquil	90150	775	1	128	92	996
				775	**1**	**128**	**92**	**996**

Domain	Region	Parroquia	Code	Urban Area	Periphery	Rural Clustered	Rural Dispersed	Total
3	1	Cuenca	10150	110			72	182
3	1	Tulcan	40150		12	36	24	72
3	1	Santa Isabel (Chaguarurco)	10850			12	60	72
3	1	Riobamba	60150	54			72	126
3	1	Guamote	60650			12	60	72
3	2	Machala	70150	55				55
3	2	Esmeraldas	80150	54		24	48	126
3	1	Ibarra	100150	54				54
3	1	Loja	110150	54				54
3	1	Saraguro	111150			12	60	72
3	2	Portoviejo	130150	54		12	60	126
3	2	Santo Domingo De Los Colorados	170650	55				55
3	1	Ambato	180150	55				55
3	1	Quero	180650		1	11	60	72
				545	**13**	**119**	**516**	**1193**

Domain	Region	Parroquia	Code	Urban Area	Periphery	Rural Clustered	Rural Dispersed	Total
4	1	Gualaceo	10350			12	61	73
4	2	Milagro	91050	56				56
4	2	Santa Elena	91750	55		64	12	131
4	1	Cotacachi	100350		24		48	72
4	1	Catamayo	110350	55				55
4	2	Quevedo	120550	54				54
4	2	Jipijapa	130650			12	60	72
4	2	Manta	130850	56				56

4	2	Montecristi	130950	57				57
4	1	Cayambe	170250	55				55
4	1	Sangolqui	170550	54				54
				442	**24**	**88**	**181**	**735**
Domain	Region	Parroquia	Code	Urban Area	Periphery	Rural Clustered	Rural Dispersed	Total
5	1	San Jose De Chimbo	20350			36	36	72
5	1	La Troncal	30450	54				54
5	1	San Gabriel	40550		24	36	12	72
5	2	Pinas	71050				76	76
5	2	Santa Rosa	71250	54				54
5	2	Rosa Zarate (Quininde)	80450		36		36	72
5	2	Velasco Ibarra(Cab. En El Empalme)	90850			24	48	72
5	2	Santa Lucia	91850	54				54
5	2	El Salitre (Las Ramas)	91950				72	72
5	2	General Villamil (Playas)	92150	55				55
5	1	Cariamanga	110250			24	48	72
5	1	Zapotillo	111350			11	61	72
5	2	Catarama/Urdaneta	120650			36	36	72
5	2	Ventanas	120750	54				54
5	2	Junin	130750			25	47	72
5	2	Bahia De Caraquez	131450			49	24	73
5	2	San Vicente	131458	54				54
5	1	San Antonio	170180	54				54
5	1	Baños	180250	55				55
				434	**60**	**241**	**496**	**1231**
Domain	Region	Parroquia	Code	Urban Area	Periphery	Rural Clustered	Rural Dispersed	Total
6	3	Macas	140150	54				54
6	3	Gualaquiza	140250			36	29	65
6	3	Sucua	140650	54				54
6	3	San Juan Bosco	140850			23	49	72
6	3	Tena	150150	54				54

6	3	Puyo	160150	110		24	49	183
6	3	Zamora	190150	54				54
6	3	Nueva Loja	210150		36		36	72
				326	**36**	**83**	**163**	**608**
		Coastal		1542	37	374	611	2564
		Andean		1410	82	263	883	2638
		Amazon		326	36	83	163	608
				3278	**155**	**720**	**1657**	**5810**

Appendix 3: Household asset-well-being model calibration results

Model 1a – global

N = 3872 Adjusted R^2 = 0.283 Std. Error of the Estimate = 0.597

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.341	.066		173.040	<.001			
H1_EDUL	-.007	.007	-.012	-.883	.377	+	.950	1.053
H2_LITS	.358	.056	.093	6.364	<.001	+	.862	1.161
H3_FTRN	.351	.040	.128	8.837	<.001	+	.889	1.125
H4_HLTH	-.001	.003	-.005	-.374	.709	-	.977	1.024
S1_TIME	-.079	.028	-.039	-2.855	.004	+	.983	1.018
N1_LOWN	<.001	<.001	<.001	.021	.983	+	.414	2.417
N1_LRNT	<.001	<.001	-.023	-1.656	.098	+	.975	1.026
N2_LCOW	.002	.001	.030	1.362	.173	+	.385	2.600
N3_LMED	-.004	.002	-.029	-1.890	.059	+	.810	1.234
N4_LSML	-.002	<.001	-.076	-5.044	<.001	+	.824	1.214
N5_LDFT	-.034	.010	-.058	-3.300	.001	+	.597	1.676
N6_AGWK	-.268	.041	-.094	-6.602	<.001		.912	1.097
P1_NBED	.483	.026	.270	18.630	<.001	+	.881	1.135
P2_ELEC	.011	.036	.005	.314	.754	+	.770	1.299
P3_CPBS	<.001	<.001	.087	5.850	<.001		.833	1.200
P4_CPAG	<.001	<.001	.019	1.217	.224	+	.752	1.329
F1_LPDM	.249	.025	.144	9.983	<.001	+	.888	1.127
F2_LPSC	<.001	<.001	.026	1.820	.069	+	.935	1.069
F3_TRDM	-.132	.025	-.080	-5.310	<.001		.813	1.230
F4_TRSC	<.001	<.001	.053	3.505	<.001	+	.798	1.253
F5_RTDM	-.016	.042	-.006	-.382	.702	+	.795	1.257
F6_RTSC	<.001	<.001	.053	3.516	<.001	+	.825	1.212
F7_PNDM	-.083	.062	-.028	-1.340	.180	+	.414	2.417
F8_PNSC	<.001	<.001	.036	1.685	.092	+	.412	2.430
F9_CRDM	.098	.022	.066	4.511	<.001		.856	1.168
F10_CRSC	<.001	<.001	.036	2.284	.022	+	.747	1.339

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

Model 1b – global, weighted

N = 3872 Adjusted R^2 = .290 Std. Error of the Estimate = 11.912

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.320	.066		170.658	<.001			
H1_EDUL	-.005	.007	-.009	-.652	.515	+	.951	1.051
H2_LITS	.387	.055	.102	7.020	<.001	+	.867	1.154
H3_FTRN	.360	.040	.129	8.951	<.001	+	.885	1.130
H4_HLTH	<.001	.003	-.002	-.138	.890	-	.972	1.029
S1_TIME	-.105	.028	-.051	-3.745	<.001	+	.978	1.022
N1_LOWN	<.001	<.001	<.001	.016	.988	+	.408	2.453
N1_LRNT	<.001	<.001	-.020	-1.496	.135	+	.985	1.015
N2_LCOW	.002	.001	.032	1.493	.135	+	.408	2.448
N3_LMED	-.003	.002	-.021	-1.350	.177	+	.792	1.262
N4_LSML	-.003	.001	-.076	-5.112	<.001	+	.828	1.208
N5_LDFT	-.039	.011	-.061	-3.442	.001	+	.593	1.685
N6_AGWK	-.306	.041	-.106	-7.414	<.001		.903	1.108
P1_NBED	.465	.026	.262	18.031	<.001	+	.870	1.150
P2_ELEC	.027	.039	.011	.696	.487	+	.763	1.311
P3_CPBS	<.001	<.001	.100	6.701	<.001		.827	1.209
P4_CPAG	<.001	<.001	.011	.692	.489	+	.749	1.335
F1_LPDM	.246	.025	.140	9.719	<.001	+	.878	1.139
F2_LPSC	<.001	<.001	.032	2.297	.022	+	.929	1.077
F3_TRDM	-.111	.024	-.069	-4.581	<.001		.820	1.219
F4_TRSC	<.001	<.001	.046	3.074	.002	+	.810	1.235
F5_RTDM	.020	.045	.007	.458	.647	+	.772	1.295
F6_RTSC	<.001	<.001	.047	3.093	.002	+	.798	1.253
F7_PNDM	-.135	.062	-.046	-2.169	.030	+	.412	2.427
F8_PNSC	<.001	<.001	.038	1.807	.071	+	.409	2.445
F9_CRDM	.111	.022	.074	5.116	<.001		.872	1.147
F10_CRSC	<.001	<.001	.025	1.594	.111	+	.742	1.347

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

Model 1c – global urban

N = 2215 Adjusted R^2 = .258 Std. Error of the Estimate =

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.173	.207		53.950	<.001			
H1_EDUL	.005	.009	.010	.544	.586	+	.976	1.024
H2_LITS	.269	.087	.058	3.080	.002	+	.949	1.054
H3_FTRN	.294	.044	.129	6.703	<.001	+	.906	1.103
H4_HLTH	-.004	.004	-.018	-.977	.329	-	.983	1.017
S1_TIME	-.025	.035	-.013	-.704	.481	+	.983	1.017
N1_LOWN	<.001	<.001	-.103	-2.749	.006	+	.238	4.200
N1_LRNT	<.001	<.001	-.025	-1.259	.208	+	.864	1.157
N2_LCOW	.007	.003	.094	2.257	.024	+	.192	5.207
N3_LMED	-.013	.009	-.028	-1.330	.184	+	.770	1.299
N4_LSML	-.003	.001	-.050	-2.387	.017	+	.763	1.311
N5_LDFT	-.009	.030	-.009	-.291	.771	+	.375	2.669
N6_AGWK	-.198	.117	-.031	-1.696	.090		.978	1.022
P1_NBED	.466	.031	.299	15.123	<.001	+	.858	1.165
P2_ELEC	.259	.194	.025	1.336	.182	+	.982	1.019
P3_CPBS	<.001	<.001	.107	5.284	<.001		.823	1.215
P4_CPAG	<.001	<.001	.033	1.358	.175	+	.560	1.787
F1_LPDM	.242	.030	.157	8.080	<.001	+	.883	1.133
F2_LPSC	<.001	<.001	.031	1.603	.109	+	.918	1.089
F3_TRDM	-.090	.032	-.058	-2.817	.005		.782	1.278
F4_TRSC	<.001	<.001	.041	1.945	.052	+	.755	1.324
F5_RTDM	-.050	.047	-.022	-1.070	.285	+	.794	1.259
F6_RTSC	<.001	<.001	.068	3.369	.001	+	.821	1.218
F7_PNDM	-.160	.066	-.069	-2.418	.016	+	.407	2.459
F8_PNSC	<.001	<.001	.055	1.898	.058	+	.400	2.503
F9_CRDM	.108	.028	.078	3.893	<.001		.841	1.189
F10_CRSC	<.001	<.001	.033	1.526	.127	+	.733	1.365

Model 1d – global urban weighted

N = 2215 Adjusted R^2 = .254 Std. Error of the Estimate = 12.160

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.096	.202		54.873	<.001			
H1_EDUL	.005	.009	.010	.548	.584	+	.973	1.028
H2_LITS	.312	.083	.070	3.744	<.001	+	.955	1.048
H3_FTRN	.288	.046	.122	6.293	<.001	+	.895	1.117
H4_HLTH	-.004	.004	-.019	-1.039	.299	-	.984	1.016
S1_TIME	-.045	.035	-.024	-1.277	.202	+	.977	1.024
N1_LOWN	<.001	<.001	-.097	-2.373	.018	+	.200	5.003
N1_LRNT	<.001	<.001	-.046	-2.193	.028	+	.772	1.295
N2_LCOW	.004	.004	.038	.889	.374	+	.182	5.501
N3_LMED	-.007	.009	-.016	-.767	.443	+	.756	1.324
N4_LSML	-.002	.001	-.035	-1.674	.094	+	.774	1.292
N5_LDFT	.053	.039	.043	1.354	.176	+	.339	2.946
N6_AGWK	-.179	.116	-.029	-1.544	.123		.981	1.019
P1_NBED	.464	.031	.297	14.930	<.001	+	.850	1.176
P2_ELEC	.320	.190	.031	1.684	.092	+	.983	1.017
P3_CPBS	<.001	<.001	.112	5.523	<.001		.816	1.225
P4_CPAG	<.001	<.001	.020	.800	.424	+	.555	1.801
F1_LPDM	.226	.031	.145	7.384	<.001	+	.873	1.145
F2_LPSC	<.001	<.001	.042	2.202	.028	+	.910	1.099
F3_TRDM	-.088	.032	-.058	-2.786	.005		.788	1.268
F4_TRSC	<.001	<.001	.033	1.578	.115	+	.766	1.306
F5_RTDM	.001	.051	<.001	.010	.992	+	.776	1.289
F6_RTSC	<.001	<.001	.057	2.753	.006	+	.799	1.251
F7_PNDM	-.170	.069	-.071	-2.449	.014	+	.400	2.503
F8_PNSC	<.001	<.001	.045	1.551	.121	+	.393	2.545
F9_CRDM	.114	.028	.081	4.093	<.001		.852	1.173
F10_CRSC	<.001	<.001	.033	1.522	.128	+	.716	1.396

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Area = 1

Model 1e – global rural

N = 1657 Adjusted R^2 = .196 Std. Error of the Estimate = 0.608

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.368	.085		134.025	<.001			
H1_EDUL	-.018	.012	-.036	-1.547	.122	+	.881	1.135
H2_LITS	.329	.076	.105	4.334	<.001	+	.822	1.217
H3_FTRN	.337	.088	.088	3.812	<.001	+	.915	1.093
H4_HLTH	.003	.004	.014	.643	.520	-	.963	1.038
S1_TIME	-.137	.044	-.070	-3.098	.002	+	.958	1.043
N1_LOWN	<.001	<.001	.078	2.535	.011	+	.519	1.927
N1_LRNT	<.001	<.001	-.009	-.418	.676	+	.973	1.028
N2_LCOW	<.001	.002	-.010	-.296	.767	+	.470	2.129
N3_LMED	-.002	.002	-.018	-.760	.447	+	.845	1.184
N4_LSML	-.001	.001	-.053	-2.262	.024	+	.883	1.132
N5_LDFT	-.028	.011	-.066	-2.483	.013	+	.688	1.454
N6_AGWK	-.165	.046	-.082	-3.598	<.001		.935	1.070
P1_NBED	.518	.046	.257	11.258	<.001	+	.933	1.072
P2_ELEC	-.067	.039	-.042	-1.744	.081	+	.822	1.217
P3_CPBS	<.001	<.001	.056	2.387	.017		.879	1.137
P4_CPAG	<.001	<.001	.026	1.058	.290	+	.810	1.234
F1_LPDM	.229	.043	.123	5.324	<.001	+	.912	1.096
F2_LPSC	<.001	<.001	.020	.863	.388	+	.946	1.057
F3_TRDM	-.207	.040	-.128	-5.147	<.001		.787	1.270
F4_TRSC	<.001	<.001	.086	3.511	<.001	+	.801	1.249
F5_RTDM	.005		.001	.055	.956	+	.744	1.344
F6_RTSC	<.001	<.001	.031	1.212	.226	+	.765	1.308
F7_PNDM	.040	.166	.008	.238	.812	+	.401	2.494
F8_PNSC	<.001	<.001	.012	.341	.733	+	.402	2.485
F9_CRDM	.097	.035	.066	2.780	.005		.860	1.163
F10_CRSC	<.001	<.001	.039	1.568	.117	+	.774	1.293

Model 1f – global rural weighted

N = 1657 Adjusted R^2 = .198 Std. Error of the Estimate = 11.050

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.336	.082		138.404	<.001			
H1_EDUL	-.013	.012	-.027	-1.152	.249	+	.873	1.146
H2_LITS	.332	.072	.112	4.601	<.001	+	.811	1.233
H3_FTRN	.408	.091	.103	4.502	<.001	+	.922	1.085
H4_HLTH	.006	.004	.034	1.519	.129	-	.943	1.060
S1_TIME	-.181	.046	-.088	-3.921	<.001	+	.953	1.049
N1_LOWN	<.001	<.001	.071	2.274	.023	+	.491	2.037
N1_LRNT	<.001	<.001	.005	.247	.805	+	.989	1.011
N2_LCOW	.001	.001	.015	.476	.634	+	.470	2.126
N3_LMED	<.001	.002	-.002	-.079	.937	+	.823	1.216
N4_LSML	-.001	.001	-.050	-2.159	.031	+	.887	1.128
N5_LDFT	-.030	.011	-.071	-2.649	.008	+	.679	1.473
N6_AGWK	-.167	.043	-.088	-3.851	<.001		.922	1.084
P1_NBED	.480	.046	.239	10.444	<.001	+	.924	1.082
P2_ELEC	-.074	.039	-.046	-1.898	.058	+	.813	1.229
P3_CPBS	<.001	<.001	.072	3.076	.002		.888	1.126
P4_CPAG	<.001	<.001	.030	1.203	.229	+	.794	1.260
F1_LPDM	.242	.044	.126	5.460	<.001	+	.907	1.103
F2_LPSC	<.001	<.001	.018	.802	.423	+	.962	1.039
F3_TRDM	-.168	.038	-.110	-4.433	<.001		.793	1.261
F4_TRSC	<.001	<.001	.084	3.477	.001	+	.823	1.215
F5_RTDM	.044	.097	.012	.450	.652	+	.650	1.538
F6_RTSC	<.001	<.001	.021	.764	.445	+	.667	1.500
F7_PNDM	-.160	.176	-.032	-.914	.361	+	.385	2.600
F8_PNSC	<.001	<.001	.011	.320	.749	+	.384	2.607
F9_CRDM	.117	.034	.081	3.460	.001		.877	1.140
F10_CRSC	<.001	<.001	.012	.491	.623	+	.773	1.294

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Area ~= 1

Model 1g – Regional Andes

N = 1778 Adjusted R^2 = .316 Std. Error of the Estimate = .533

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.432	.085		134.613	<.001			
H1_EDUL	-.009	.009	-.019	-.923	.356	+	.947	1.056
H2_LITS	.397	.070	.120	5.654	<.001	+	.848	1.179
H3_FTRN	.420	.061	.143	6.923	<.001	+	.904	1.106
H4_HLTH	-.002	.004	-.009	-.455	.649	-	.961	1.041
S1_TIME	-.122	.039	-.063	-3.145	.002	+	.970	1.031
N1_LOWN	<.001	<.001	-.003	-.110	.913	+	.442	2.265
N1_LRNT	<.001	<.001	-.007	-.366	.714	+	.988	1.012
N2_LCOW	.003	.002	.052	1.722	.085	+	.414	2.414
N3_LMED	-.009	.006	-.036	-1.580	.114	+	.747	1.339
N4_LSML	-.004	.001	-.096	-3.840	<.001	+	.611	1.638
N5_LDFT	-.014	.016	-.023	-.922	.357	+	.600	1.667
N6_AGWK	-.317	.050	-.133	-6.314	<.001		.873	1.145
P1_NBED	.433	.033	.271	13.041	<.001	+	.892	1.122
P2_ELEC	.031	.050	.014	.617	.537	+	.729	1.372
P3_CPBS	<.001	<.001	.112	5.381	<.001		.895	1.117
P4_CPAG	<.001	<.001	.005	.244	.807	+	.838	1.193
F1_LPDM	.214	.036	.125	5.900	<.001	+	.862	1.160
F2_LPSC	<.001	<.001	.020	.989	.323	+	.922	1.085
F3_TRDM	-.100	.032	-.068	-3.177	.002		.832	1.201
F4_TRSC	<.001	<.001	.050	2.324	.020	+	.829	1.206
F5_RTDM	.065	.070	.021	.933	.351	+	.755	1.324
F6_RTSC	<.001	<.001	.047	2.083	.037	+	.767	1.304
F7_PNDM	-.137	.097	-.046	-1.412	.158	+	.359	2.786
F8_PNSC	<.001	<.001	.033	1.026	.305	+	.361	2.766

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Andes

Model 1h – Regional Andes weighted

N = 1778 Adjusted R^2 = .317 Std. Error of the Estimate = 11.831

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.428	.088		129.471	<.001			
H1_EDUL	-.005	.009	-.010	-.491	.623	+	.949	1.053
H2_LITS	.415	.071	.124	5.876	<.001	+	.859	1.164
H3_FTRN	.453	.059	.158	7.620	<.001	+	.896	1.116
H4_HLTH	.001	.004	.004	.217	.828	-	.948	1.054
S1_TIME	-.166	.039	-.084	-4.223	<.001	+	.960	1.042
N1_LOWN	<.001	<.001	-.013	-.444	.657	+	.453	2.208
N1_LRNT	<.001	<.001	-.013	-.638	.524	+	.989	1.011
N2_LCOW	.003	.002	.060	2.051	.040	+	.448	2.233
N3_LMED	-.008	.006	-.027	-1.206	.228	+	.745	1.342
N4_LSML	-.003	.001	-.070	-2.804	.005	+	.620	1.612
N5_LDFT	-.023	.017	-.034	-1.353	.176	+	.610	1.639
N6_AGWK	-.337	.052	-.137	-6.475	<.001		.860	1.163
P1_NBED	.416	.033	.261	12.455	<.001	+	.878	1.139
P2_ELEC	.040	.055	.017	.737	.461	+	.727	1.376
P3_CPBS	<.001	<.001	.131	6.407	<.001		.913	1.096
P4_CPAG	<.001	<.001	-.002	-.092	.927	+	.855	1.170
F1_LPDM	.212	.037	.122	5.759	<.001	+	.854	1.171
F2_LPSC	<.001	<.001	.022	1.066	.287	+	.916	1.092
F3_TRDM	-.057	.032	-.039	-1.787	.074		.826	1.210
F4_TRSC	<.001	<.001	.046	2.160	.031	+	.834	1.199
F5_RTDM	.017	.072	.005	.238	.812	+	.744	1.345
F6_RTSC	<.001	<.001	.046	2.049	.041	+	.753	1.329
F7_PNDM	-.233	.098	-.077	-2.384	.017	+	.372	2.690
F8_PNSC	<.001	<.001	.052	1.610	.107	+	.374	2.671
F9_CRDM	.053	.029	.038	1.847	.065		.915	1.093
F10_CRSC	<.001	<.001	.056	2.642	.008	+	.847	1.180

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Andes

Model 1i – Regional coastal

N = 1659 Adjusted R^2 = .279 Std. Error of the Estimate = .657

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.223	.117		95.924	<.001			
H1_EDUL	.002	.013	.003	.129	.898	+	.925	1.081
H2_LITS	.316	.099	.072	3.203	.001	+	.858	1.166
H3_FTRN	.321	.064	.112	5.003	<.001	+	.863	1.158
H4_HLTH	.001	.004	.003	.159	.873	-	.973	1.028
S1_TIME	-.069	.046	-.031	-1.487	.137	+	.972	1.029
N1_LOWN	<.001	<.001	.008	.202	.840	+	.255	3.916
N1_LRNT	<.001	<.001	-.020	-.889	.374	+	.873	1.145
N2_LCOW	-.001	.004	-.013	-.303	.762	+	.236	4.238
N3_LMED	-.001	.003	-.008	-.342	.733	+	.718	1.393
N4_LSML	-.002	.001	-.054	-2.404	.016	+	.852	1.173
N5_LDFT	-.049	.018	-.075	-2.633	.009	+	.541	1.850
N6_AGWK	-.165	.073	-.049	-2.260	.024		.912	1.097
P1_NBED	.596	.047	.286	12.652	<.001	+	.849	1.178
P2_ELEC	-.033	.068	-.012	-.490	.624	+	.782	1.278
P3_CPBS	<.001	<.001	.082	3.322	.001		.714	1.400
P4_CPAG	<.001	<.001	.014	.531	.596	+	.650	1.538
F1_LPDM	.290	.040	.163	7.337	<.001	+	.882	1.133
F2_LPSC	<.001	<.001	.041	1.871	.062	+	.924	1.083
F3_TRDM	-.196	.043	-.109	-4.534	<.001		.758	1.319
F4_TRSC	<.001	<.001	.063	2.530	.012	+	.698	1.433
F5_RTDM	.065	.065	.024	1.004	.315	+	.786	1.272
F6_RTSC	<.001	<.001	.040	1.728	.084	+	.832	1.202
F7_PNDM	-.062	.095	-.021	-.648	.517	+	.403	2.484
F8_PNSC	<.001	<.001	.037	1.112	.266	+	.395	2.529
F9_CRDM	.172	.037	.107	4.624	<.001		.814	1.228
F10_CRSC	<.001	<.001	.011	.435	.664	+	.634	1.578

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Coastal

Model 1j – Regional Coastal weighted

N = 1659   Adjusted R^2 = .295   Std. Error of the Estimate = 12.810

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.080	.120		91.976	<.001			
H1_EDUL	.005	.013	.008	.358	.720	+	.932	1.073
H2_LITS	.363	.100	.081	3.651	<.001	+	.861	1.162
H3_FTRN	.331	.062	.120	5.375	<.001	+	.859	1.164
H4_HLTH	<.001	.004	-.001	-.042	.966	-	.977	1.024
S1_TIME	-.056	.046	-.025	-1.208	.227	+	.976	1.024
N1_LOWN	<.001	<.001	.006	.158	.875	+	.251	3.989
N1_LRNT	<.001	<.001	-.018	-.840	.401	+	.945	1.059
N2_LCOW	-.001	.004	-.010	-.227	.821	+	.239	4.183
N3_LMED	.001	.003	.010	.382	.702	+	.680	1.471
N4_LSML	-.002	.001	-.067	-2.975	.003	+	.844	1.184
N5_LDFT	-.050	.019	-.076	-2.677	.007	+	.532	1.879
N6_AGWK	-.233	.078	-.064	-2.986	.003		.926	1.080
P1_NBED	.556	.046	.271	12.002	<.001	+	.835	1.197
P2_ELEC	.024	.074	.008	.329	.742	+	.765	1.307
P3_CPBS	<.001	<.001	.079	3.163	.002		.685	1.460
P4_CPAG	<.001	<.001	.023	.862	.389	+	.604	1.655
F1_LPDM	.296	.039	.166	7.533	<.001	+	.877	1.140
F2_LPSC	<.001	<.001	.046	2.133	.033	+	.913	1.095
F3_TRDM	-.198	.042	-.111	-4.730	<.001		.774	1.292
F4_TRSC	<.001	<.001	.058	2.400	.016	+	.725	1.380
F5_RTDM	.100	.064	.037	1.561	.119	+	.772	1.295
F6_RTSC	<.001	<.001	.035	1.549	.122	+	.817	1.223
F7_PNDM	-.041	.093	-.014	-.436	.663	+	.397	2.521
F8_PNSC	<.001	<.001	.031	.936	.350	+	.388	2.575
F9_CRDM	.205	.037	.127	5.554	<.001		.809	1.236
F10_CRSC	<.001	<.001	.003	.117	.907	+	.603	1.658

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Coastal

Model 1k – Regional Amazon

N = 435 Adjusted R^2 = .249 Std. Error of the Estimate = .576

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.204	.208		53.938	<.001			
H1_EDUL	.011	.021	.023	.532	.595	+	.964	1.037
H2_LITS	.310	.190	.074	1.629	.104	+	.836	1.197
H3_FTRN	.370	.095	.177	3.913	<.001	+	.848	1.179
H4_HLTH	-.007	.009	-.032	-.731	.465	-	.916	1.092
S1_TIME	.021	.071	.013	.291	.771	+	.926	1.080
N1_LOWN	<.001	<.001	.059	.985	.325	+	.477	2.099
N1_LRNT	<.001	<.001	-.007	-.170	.865	+	.911	1.098
N2_LCOW	.001	.004	.020	.283	.777	+	.338	2.958
N3_LMED	-.004	.012	-.018	-.362	.718	+	.690	1.450
N4_LSML	-.002	.001	-.064	-1.337	.182	+	.754	1.326
N5_LDFT	-.025	.023	-.062	-1.099	.272	+	.538	1.858
N6_AGWK	-.247	.143	-.077	-1.729	.085		.877	1.141
P1_NBED	.455	.070	.290	6.505	<.001	+	.868	1.152
P2_ELEC	.004	.081	.003	.049	.961	+	.659	1.518
P3_CPBS	<.001	<.001	.029	.661	.509		.888	1.127
P4_CPAG	<.001	<.001	.081	1.597	.111	+	.674	1.484
F1_LPDM	.225	.071	.142	3.156	.002	+	.855	1.170
F2_LPSC	<.001	<.001	<.001	-.010	.992	+	.854	1.171
F3_TRDM	-.104	.086	-.058	-1.215	.225		.771	1.297
F4_TRSC	<.001	<.001	.079	1.680	.094	+	.789	1.268
F5_RTDM	-.253	.106	-.127	-2.382	.018	+	.613	1.632
F6_RTSC	<.001	<.001	.079	1.513	.131	+	.643	1.556
F7_PNDM	.040	.203	.013	.197	.844	+	.384	2.602
F8_PNSC	<.001	<.001	.015	.228	.819	+	.392	2.552
F9_CRDM	.088	.065	.066	1.365	.173		.740	1.351
F10_CRSC	<.001	<.001	.051	1.034	.302	+	.713	1.402

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Amazon

Model 1l – Regional Amazon weighted

N = 435 Adjusted R^2 = .289 Std. Error of the Estimate = 5.971

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.350	.173		65.605	<.001			
H1_EDUL	.015	.020	.033	.770	.442	+	.907	1.102
H2_LITS	.200	.161	.058	1.241	.215	+	.739	1.354
H3_FTRN	.271	.109	.110	2.483	.013	+	.831	1.203
H4_HLTH	-.010	.008	-.058	-1.302	.194	-	.835	1.198
S1_TIME	-.081	.066	-.054	-1.231	.219	+	.853	1.172
N1_LOWN	<.001	<.001	.108	2.155	.032	+	.653	1.531
N1_LRNT	<.001	<.001	-.028	-.652	.515	+	.870	1.150
N2_LCOW	-.002	.003	-.040	-.658	.511	+	.438	2.282
N3_LMED	.005	.009	.024	.483	.629	+	.688	1.454
N4_LSML	-.002	.001	-.085	-1.832	.068	+	.758	1.319
N5_LDFT	-.030	.019	-.081	-1.522	.129	+	.578	1.729
N6_AGWK	-.381	.118	-.140	-3.231	.001		.874	1.145
P1_NBED	.572	.069	.373	8.258	<.001	+	.805	1.243
P2_ELEC	.011	.066	.008	.163	.871	+	.645	1.550
P3_CPBS	<.001	<.001	.044	1.021	.308		.883	1.132
P4_CPAG	<.001	<.001	.083	1.698	.090	+	.682	1.465
F1_LPDM	.185	.073	.113	2.550	.011	+	.832	1.202
F2_LPSC	<.001	<.001	.024	.570	.569	+	.894	1.119
F3_TRDM	-.138	.089	-.072	-1.548	.122		.762	1.313
F4_TRSC	<.001	<.001	.057	1.235	.218	+	.777	1.288
F5_RTDM	-.436	.122	-.191	-3.587	<.001	+	.577	1.733
F6_RTSC	<.001	<.001	.100	1.912	.057	+	.601	1.664
F7_PNDM	.112	.250	.029	.451	.652	+	.386	2.588
F8_PNSC	<.001	<.001	.010	.155	.877	+	.403	2.484
F9_CRDM	.048	.063	.036	.756	.450		.732	1.366
F10_CRSC	<.001	<.001	.027	.531	.596	+	.640	1.562

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Amazon

Model 1 – urban regional, Andes

N = 1038 Adjusted R Square = .297 Std. Error of the Estimate = 0.517

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	10.921	.320		34.168	<.001			
H1_EDUL	.004	.012	.009	.333	.739	+	.973	1.027
H2_LITS	.368	.104	.095	3.533	<.001	+	.944	1.060
H3_FTRN	.342	.065	.145	5.289	<.001	+	.907	1.103
H4_HLTH	<.001	.005	.001	.040	.968	-	.972	1.029
S1_TIME	-.112	.050	-.060	-2.239	.025	+	.954	1.049
N1_LOWN	<.001	<.001	-.079	-2.778	.006	+	.833	1.200
N1_LRNT	<.001	<.001	-.005	-.176	.860	+	.847	1.181
N2_LCOW	.016	.016	.035	1.016	.310	+	.563	1.777
N3_LMED	-.024	.014	-.058	-1.719	.086	+	.586	1.706
N4_LSML	-.001	.003	-.008	-.276	.782	+	.736	1.359
N5_LDFT	.090	.084	.030	1.080	.280	+	.887	1.127
N6_AGWK	-.283	.148	-.050	-1.907	.057		.967	1.034
P1_NBED	.462	.040	.322	11.444	<.001	+	.858	1.165
P2_ELEC	.569	.301	.050	1.889	.059	+	.983	1.017
P3_CPBS	<.001	<.001	.136	4.972	<.001		.911	1.097
P4_CPAG	<.001	<.001	.011	.376	.707	+	.779	1.283
F1_LPDM	.223	.043	.145	5.141	<.001	+	.847	1.180
F2_LPSC	<.001	<.001	.019	.690	.490	+	.900	1.111
F3_TRDM	-.079	.040	-.057	-1.952	.051		.809	1.237
F4_TRSC	<.001	<.001	.047	1.622	.105	+	.804	1.244
F5_RTDM	.036	.087	.013	.414	.679	+	.736	1.359
F6_RTSC	<.001	<.001	.050	1.651	.099	+	.735	1.360
F7_PNDM	-.172	.107	-.070	-1.598	.110	+	.355	2.815
F8_PNSC	<.001	<.001	.032	.737	.461	+	.357	2.803
F9_CRDM	.057	.037	.043	1.532	.126		.879	1.138
F10_CRSC	<.001	<.001	.072	2.443	.015	+	.792	1.263

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Andes

Model 1 – urban regional Andes weighted

N = 1038 Adjusted R^2 = .286 Std. Error of the Estimate = 12.258

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	10.878	.329		33.034	<.001			
H1_EDUL	.004	.012	.008	.298	.766	+	.971	1.030
H2_LITS	.375	.105	.097	3.583	<.001	+	.946	1.057
H3_FTRN	.361	.066	.150	5.435	<.001	+	.899	1.112
H4_HLTH	<.001	.005	<.001	-.010	.992	-	.971	1.030
S1_TIME	-.114	.050	-.062	-2.293	.022	+	.949	1.053
N1_LOWN	<.001	<.001	-.086	-2.976	.003	+	.823	1.215
N1_LRNT	<.001	<.001	-.003	-.120	.905	+	.848	1.179
N2_LCOW	.010	.015	.024	.659	.510	+	.510	1.961
N3_LMED	-.017	.014	-.045	-1.267	.206	+	.534	1.872
N4_LSML	<.001	.003	.003	.086	.932	+	.703	1.422
N5_LDFT	.095	.084	.032	1.131	.258	+	.881	1.135
N6_AGWK	-.249	.142	-.047	-1.758	.079		.965	1.036
P1_NBED	.442	.041	.307	10.775	<.001	+	.846	1.182
P2_ELEC	.609	.311	.052	1.956	.051	+	.985	1.015
P3_CPBS	<.001	<.001	.152	5.571	<.001		.919	1.088
P4_CPAG	<.001	<.001	.009	.304	.761	+	.785	1.274
F1_LPDM	.198	.045	.126	4.416	<.001	+	.841	1.189
F2_LPSC	<.001	<.001	.021	.774	.439	+	.896	1.117
F3_TRDM	-.047	.041	-.033	-1.134	.257		.812	1.232
F4_TRSC	<.001	<.001	.041	1.398	.162	+	.814	1.229
F5_RTDM	.002	.090	.001	.018	.986	+	.745	1.343
F6_RTSC	<.001	<.001	.051	1.692	.091	+	.749	1.335
F7_PNDM	-.179	.114	-.069	-1.566	.118	+	.360	2.780
F8_PNSC	<.001	<.001	.032	.742	.458	+	.362	2.763
F9_CRDM	.062	.038	.046	1.636	.102		.884	1.132
F10_CRSC	<.001	<.001	.075	2.533	.011	+	.776	1.289

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Andes

Model 1 – urban regional, coastal

N = 945 Adjusted R^2 = .259 Std. Error of the Estimate = 0.622

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.298	.283		39.858	<.001			
H1_EDUL	.018	.017	.031	1.074	.283	+	.941	1.063
H2_LITS	.131	.157	.025	.837	.403	+	.902	1.108
H3_FTRN	.284	.071	.118	3.982	<.001	+	.891	1.122
H4_HLTH	-.006	.005	-.031	-1.079	.281	-	.972	1.029
S1_TIME	-.015	.055	-.008	-.271	.786	+	.980	1.020
N1_LOWN	<.001	<.001	-.118	-1.372	.170	+	.106	9.393
N1_LRNT	<.001	<.001	-.046	-1.277	.202	+	.616	1.624
N2_LCOW	.005	.006	.068	.760	.447	+	.097	10.321
N3_LMED	-.002	.018	-.005	-.133	.894	+	.674	1.484
N4_LSML	-.004	.002	-.063	-1.872	.062	+	.696	1.437
N5_LDFT	.025	.059	.028	.434	.664	+	.193	5.170
N6_AGWK	-.032	.195	-.005	-.165	.869		.939	1.065
P1_NBED	.538	.053	.310	10.158	<.001	+	.844	1.185
P2_ELEC	.062	.263	.007	.237	.812	+	.939	1.065
P3_CPBS	<.001	<.001	.101	2.970	.003		.672	1.488
P4_CPAG	<.001	<.001	.022	.511	.610	+	.440	2.274
F1_LPDM	.272	.047	.173	5.795	<.001	+	.880	1.137
F2_LPSC	<.001	<.001	.064	2.134	.033	+	.880	1.136
F3_TRDM	-.128	.056	-.077	-2.289	.022		.693	1.443
F4_TRSC	<.001	<.001	.020	.572	.568	+	.637	1.569
F5_RTDM	.039	.070	.018	.564	.573	+	.780	1.283
F6_RTSC	<.001	<.001	.057	1.837	.067	+	.825	1.213
F7_PNDM	-.150	.097	-.068	-1.546	.123	+	.401	2.494
F8_PNSC	<.001	<.001	.070	1.543	.123	+	.385	2.598
F9_CRDM	.192	.046	.130	4.176	<.001		.810	1.235
F10_CRSC	<.001	<.001	.013	.351	.726	+	.578	1.730

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Coastal

Model 1 – urban regional coastal weighted

N = 945   Adjusted R^2 = .254   Std. Error of the Estimate = 13.043

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.145	.283		39.378	<.001			
H1_EDUL	.023	.017	.039	1.339	.181	+	.940	1.063
H2_LITS	.273	.157	.051	1.736	.083	+	.898	1.113
H3_FTRN	.266	.071	.112	3.749	<.001	+	.880	1.137
H4_HLTH	-.005	.006	-.027	-.939	.348	-	.975	1.026
S1_TIME	-.015	.055	-.008	-.268	.789	+	.976	1.025
N1_LOWN	<.001	<.001	-.106	-1.327	.185	+	.124	8.083
N1_LRNT	<.001	<.001	-.066	-1.807	.071	+	.601	1.665
N2_LCOW	.002	.005	.030	.384	.701	+	.128	7.785
N3_LMED	.004	.018	.007	.201	.841	+	.681	1.468
N4_LSML	-.003	.002	-.048	-1.470	.142	+	.739	1.354
N5_LDFT	.053	.059	.056	.906	.365	+	.208	4.816
N6_AGWK	-.070	.230	-.009	-.304	.761		.954	1.048
P1_NBED	.530	.054	.300	9.809	<.001	+	.843	1.186
P2_ELEC	.036	.265	.004	.137	.891	+	.940	1.064
P3_CPBS	<.001	<.001	.080	2.287	.022		.650	1.537
P4_CPAG	<.001	<.001	.023	.505	.614	+	.374	2.671
F1_LPDM	.267	.047	.170	5.643	<.001	+	.875	1.143
F2_LPSC	<.001	<.001	.063	2.093	.037	+	.870	1.149
F3_TRDM	-.157	.056	-.094	-2.816	.005		.709	1.411
F4_TRSC	<.001	<.001	.028	.810	.418	+	.674	1.484
F5_RTDM	.070	.071	.032	.987	.324	+	.772	1.295
F6_RTSC	<.001	<.001	.047	1.521	.129	+	.815	1.227
F7_PNDM	-.113	.101	-.050	-1.119	.263	+	.392	2.550
F8_PNSC	<.001	<.001	.056	1.229	.219	+	.379	2.638
F9_CRDM	.214	.046	.145	4.626	<.001		.805	1.242
F10_CRSC	<.001	<.001	.020	.543	.587	+	.556	1.799

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Coastal

Model 1 – urban, Amazon region

N = 232 Adjusted R^2 = .210 Std. Error of the Estimate = 0.595

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	10.563	.424		24.924	<.001			
H1_EDUL	.036	.031	.071	1.183	.238	+	.941	1.062
H2_LITS	.833	.408	.126	2.042	.042	+	.896	1.116
H3_FTRN	.387	.116	.210	3.347	.001	+	.866	1.154
H4_HLTH	-.003	.015	-.011	-.185	.853	-	.918	1.089
S1_TIME	.114	.111	.065	1.035	.302	+	.870	1.150
N1_LOWN	<.001	<.001	-.169	-1.385	.167	+	.229	4.368
N1_LRNT	<.001	<.001	.021	.286	.775	+	.660	1.515
N2_LCOW	.013	.006	.309	2.060	.041	+	.152	6.579
N3_LMED	-.007	.039	-.016	-.172	.863	+	.388	2.575
N4_LSML	-.001	.002	-.038	-.534	.594	+	.660	1.516
N5_LDFT	-.097	.068	-.176	-1.439	.152	+	.228	4.382
N6_AGWK	-.692	.538	-.079	-1.285	.200		.913	1.095
P1_NBED	.344	.098	.228	3.517	.001	+	.817	1.224
P2_ELEC						+		
P3_CPBS	<.001	<.001	-.003	-.049	.961		.875	1.143
P4_CPAG	<.001	<.001	.160	1.844	.067	+	.456	2.193
F1_LPDM	.209	.098	.141	2.142	.033	+	.792	1.263
F2_LPSC	<.001	<.001	-.026	-.370	.711	+	.670	1.492
F3_TRDM	-.069	.112	-.041	-.617	.538		.760	1.317
F4_TRSC	<.001	<.001	.089	1.328	.186	+	.758	1.319
F5_RTDM	-.162	.130	-.095	-1.250	.213	+	.591	1.691
F6_RTSC	<.001	<.001	.091	1.190	.235	+	.587	1.704
F7_PNDM	.085	.246	.034	.345	.730	+	.351	2.852
F8_PNSC	<.001	<.001	-.008	-.083	.934	+	.355	2.816
F9_CRDM	.156	.091	.116	1.714	.088		.741	1.350
F10_CRSC	<.001	<.001	.048	.677	.499	+	.675	1.481

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Amazon

The following variables are constants or have missing correlations: P2. Dummy variable for electricity.

Model 1 – urban regional Amazon weighted

N = 232 Adjusted R^2 = .238 Std. Error of the Estimate = 4.075

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	10.323	.423		24.383	<.001			
H1_EDUL	.036	.030	.070	1.185	.237	+	.944	1.060
H2_LITS	1.041	.403	.158	2.579	.011	+	.875	1.143
H3_FTRN	.415	.113	.229	3.685	<.001	+	.857	1.167
H4_HLTH	-.001	.014	-.003	-.042	.967	-	.912	1.096
S1_TIME	.095	.108	.055	.881	.379	+	.855	1.170
N1_LOWN	<.001	<.001	-.158	-1.377	.170	+	.249	4.015
N1_LRNT	<.001	<.001	.021	.322	.747	+	.776	1.289
N2_LCOW	.013	.006	.314	2.193	.029	+	.161	6.217
N3_LMED	-.001	.035	-.002	-.018	.985	+	.355	2.814
N4_LSML	-.001	.002	-.041	-.609	.543	+	.718	1.393
N5_LDFT	-.101	.064	-.202	-1.584	.115	+	.202	4.954
N6_AGWK	-.593	.633	-.056	-.937	.350		.919	1.089
P1_NBED	.368	.096	.244	3.816	<.001	+	.806	1.240
P2_ELEC						+		
P3_CPBS	<.001	<.001	.009	.152	.879		.866	1.155
P4_CPAG	<.001	<.001	.156	1.709	.089	+	.396	2.528
F1_LPDM	.157	.095	.107	1.657	.099	+	.797	1.255
F2_LPSC	<.001	<.001	-.014	-.197	.844	+	.647	1.545
F3_TRDM	-.074	.111	-.044	-.670	.504		.756	1.322
F4_TRSC	<.001	<.001	.099	1.474	.142	+	.735	1.361
F5_RTDM	-.170	.129	-.099	-1.324	.187	+	.591	1.691
F6_RTSC	<.001	<.001	.091	1.228	.221	+	.602	1.662
F7_PNDM	.174	.253	.068	.685	.494	+	.330	3.029
F8_PNSC	<.001	<.001	-.017	-.168	.866	+	.335	2.984
F9_CRDM	.176	.088	.132	2.002	.047		.758	1.320
F10_CRSC	<.001	<.001	.053	.752	.453	+	.662	1.511

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Amazon

The following variables are constants or have missing correlations: P2. Dummy variable for electricity.

Model 1 – rural, Andes

N = 740 Adjusted R^2 = .192 Std. Error of the Estimate = 0.530

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.473	.107		107.365	<.001			
H1_EDUL	-.017	.016	-.039	-1.093	.275	+	.849	1.178
H2_LITS	.360	.097	.139	3.718	<.001	+	.785	1.273
H3_FTRN	.211	.166	.043	1.271	.204	+	.940	1.064
H4_HLTH	-.001	.006	-.008	-.226	.821	-	.941	1.063
S1_TIME	-.173	.060	-.099	-2.896	.004	+	.943	1.060
N1_LOWN	<.001	<.001	.064	1.255	.210	+	.418	2.392
N1_LRNT	<.001	<.001	.011	.344	.731	+	.993	1.007
N2_LCOW	.001	.002	.030	.558	.577	+	.384	2.602
N3_LMED	-.007	.007	-.040	-.986	.324	+	.676	1.479
N4_LSML	-.002	.001	-.078	-1.926	.054	+	.671	1.489
N5_LDFT	-.012	.016	-.031	-.747	.455	+	.622	1.608
N6_AGWK	-.209	.056	-.130	-3.760	<.001		.920	1.086
P1_NBED	.377	.056	.232	6.695	<.001	+	.909	1.100
P2_ELEC	-.048	.052	-.035	-.924	.356	+	.783	1.277
P3_CPBS	<.001	<.001	.019	.489	.625		.696	1.436
P4_CPAG	<.001	<.001	.046	1.223	.222	+	.765	1.307
F1_LPDM	.190	.065	.107	2.912	.004	+	.817	1.224
F2_LPSC	<.001	<.001	-.012	-.334	.738	+	.797	1.255
F3_TRDM	-.111	.052	-.082	-2.140	.033		.738	1.354
F4_TRSC	<.001	<.001	-.003	-.090	.928	+	.751	1.331
F5_RTDM	.166	.121	.056	1.379	.168	+	.672	1.489
F6_RTSC	<.001	<.001	.023	.582	.561	+	.693	1.443
F7_PNDM	-.075	.217	-.020	-.345	.730	+	.340	2.940
F8_PNSC	<.001	<.001	.016	.272	.786	+	.325	3.076
F9_CRDM	.069	.044	.055	1.559	.119		.887	1.127
F10_CRSC	<.001	<.001	.117	2.763	.006	+	.611	1.638

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Andes

Model 1 – rural regional Andes weighted

N = 740 Adjusted R^2 = .206 Std. Error of the Estimate = 10.555

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.452	.105		109.144	<.001			
H1_EDUL	-.002	.016	-.004	-.115	.908	+	.840	1.190
H2_LITS	.352	.093	.140	3.766	<.001	+	.775	1.291
H3_FTRN	.494	.165	.102	2.993	.003	+	.922	1.084
H4_HLTH	.006	.005	.042	1.234	.218	-	.911	1.098
S1_TIME	-.282	.064	-.151	-4.438	<.001	+	.923	1.083
N1_LOWN	<.001	<.001	.049	.968	.333	+	.424	2.357
N1_LRNT	<.001	<.001	.017	.509	.611	+	.986	1.015
N2_LCOW	.002	.002	.065	1.285	.199	+	.415	2.407
N3_LMED	-.005	.007	-.028	-.707	.480	+	.676	1.479
N4_LSML	-.001	.001	-.041	-1.033	.302	+	.690	1.450
N5_LDFT	-.018	.016	-.046	-1.106	.269	+	.630	1.588
N6_AGWK	-.201	.054	-.129	-3.727	<.001		.896	1.116
P1_NBED	.375	.058	.225	6.513	<.001	+	.902	1.108
P2_ELEC	-.050	.052	-.036	-.962	.337	+	.780	1.282
P3_CPBS	<.001	<.001	.031	.790	.430		.694	1.442
P4_CPAG	<.001	<.001	.035	.940	.348	+	.785	1.274
F1_LPDM	.216	.066	.119	3.282	.001	+	.821	1.218
F2_LPSC	<.001	<.001	-.004	-.114	.909	+	.896	1.116
F3_TRDM	-.080	.052	-.060	-1.549	.122		.718	1.393
F4_TRSC	<.001	<.001	.021	.554	.580	+	.754	1.327
F5_RTDM	.121	.141	.040	.861	.389	+	.508	1.967
F6_RTSC	<.001	<.001	.004	.093	.926	+	.517	1.934
F7_PNDM	-.442	.225	-.114	-1.970	.049	+	.322	3.108
F8_PNSC	<.001	<.001	.054	.939	.348	+	.324	3.089
F9_CRDM	.061	.044	.048	1.402	.161		.905	1.105
F10_CRSC	<.001	<.001	.081	1.962	.050	+	.623	1.605

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Andes

Model 1 – rural, coastal

N = 714 Adjusted R^2 = .200 Std. Error of the Estimate = 0.689

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.175	.159		70.329	<.001			
H1_EDUL	-.019	.021	-.032	-.892	.373	+	.858	1.166
H2_LITS	.389	.135	.106	2.873	.004	+	.817	1.224
H3_FTRN	.364	.133	.098	2.732	.006	+	.867	1.153
H4_HLTH	.007	.006	.039	1.133	.258	-	.944	1.060
S1_TIME	-.105	.083	-.044	-1.270	.205	+	.926	1.080
N1_LOWN	<.001	<.001	.072	1.819	.069	+	.726	1.378
N1_LRNT	<.001	<.001	.008	.206	.837	+	.790	1.266
N2_LCOW	-.006	.005	-.053	-1.219	.223	+	.594	1.683
N3_LMED	.001	.003	.007	.176	.860	+	.737	1.357
N4_LSML	-.001	.001	-.030	-.832	.405	+	.868	1.152
N5_LDFT	-.041	.021	-.079	-1.895	.058	+	.647	1.547
N6_AGWK	-.064	.087	-.026	-.733	.464		.881	1.135
P1_NBED	.691	.097	.252	7.155	<.001	+	.903	1.107
P2_ELEC	-.115	.076	-.057	-1.527	.127	+	.813	1.230
P3_CPBS	<.001	<.001	.092	2.529	.012		.850	1.176
P4_CPAG	<.001	<.001	-.013	-.327	.744	+	.698	1.432
F1_LPDM	.266	.071	.135	3.722	<.001	+	.856	1.168
F2_LPSC	<.001	<.001	.020	.568	.570	+	.919	1.088
F3_TRDM	-.258	.069	-.140	-3.745	<.001		.798	1.254
F4_TRSC	<.001	<.001	.140	3.790	<.001	+	.821	1.219
F5_RTDM	.081	.161	.019	.503	.615	+	.788	1.269
F6_RTSC	<.001	<.001	.019	.505	.614	+	.810	1.235
F7_PNDM	.149	.310	.025	.481	.631	+	.419	2.389
F8_PNSC	<.001	<.001	.010	.197	.844	+	.423	2.362
F9_CRDM	.103	.062	.061	1.646	.100		.806	1.241
F10_CRSC	<.001	<.001	.009	.228	.820	+	.755	1.324

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Coastal

Model 1 – rural regional coastal weighted

N = 714 Adjusted R^2 = .194 Std. Error of the Estimate = 12.120

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.093	.157		70.711	<.001			
H1_EDUL	-.022	.020	-.039	-1.098	.273	+	.874	1.144
H2_LITS	.374	.131	.107	2.867	.004	+	.813	1.230
H3_FTRN	.423	.132	.115	3.207	.001	+	.873	1.146
H4_HLTH	.006	.006	.032	.921	.357	-	.936	1.069
S1_TIME	-.057	.086	-.023	-.655	.513	+	.944	1.059
N1_LOWN	<.001	<.001	.063	1.571	.117	+	.713	1.403
N1_LRNT	<.001	<.001	.023	.631	.528	+	.886	1.129
N2_LCOW	-.007	.005	-.052	-1.239	.216	+	.651	1.536
N3_LMED	.003	.003	.044	1.096	.274	+	.697	1.435
N4_LSML	-.001	.001	-.052	-1.435	.152	+	.848	1.180
N5_LDFT	-.035	.020	-.075	-1.742	.082	+	.616	1.623
N6_AGWK	-.088	.084	-.037	-1.047	.296		.899	1.112
P1_NBED	.562	.095	.210	5.909	<.001	+	.895	1.117
P2_ELEC	-.083	.076	-.041	-1.097	.273	+	.791	1.264
P3_CPBS	<.001	<.001	.132	3.625	<.001		.847	1.181
P4_CPAG	<.001	<.001	.001	.026	.979	+	.631	1.584
F1_LPDM	.264	.074	.130	3.572	<.001	+	.857	1.167
F2_LPSC	<.001	<.001	.027	.785	.433	+	.949	1.054
F3_TRDM	-.214	.064	-.124	-3.321	.001		.810	1.235
F4_TRSC	<.001	<.001	.130	3.552	<.001	+	.841	1.190
F5_RTDM	.111	.175	.025	.633	.527	+	.733	1.364
F6_RTSC	<.001	<.001	.017	.454	.650	+	.770	1.299
F7_PNDM	.235	.339	.034	.695	.487	+	.467	2.143
F8_PNSC	<.001	<.001	-.030	-.618	.537	+	.467	2.140
F9_CRDM	.131	.062	.080	2.117	.035		.790	1.266
F10_CRSC	<.001	<.001	.001	.036	.971	+	.684	1.462

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Coastal

Model 1 – rural, Amazon

N = 203 Adjusted R^2 = .219 Std. Error of the Estimate = 0.553

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.422	.246		46.351	<.001			
H1_EDUL	-.002	.030	-.005	-.072	.942	+	.913	1.096
H2_LITS	.151	.220	.048	.688	.492	+	.794	1.260
H3_FTRN	.259	.202	.089	1.279	.203	+	.806	1.241
H4_HLTH	-.013	.011	-.074	-1.122	.263	-	.887	1.127
S1_TIME	-.084	.100	-.058	-.847	.398	+	.836	1.197
N1_LOWN	<.001	<.001	.120	1.614	.108	+	.702	1.425
N1_LRNT	<.001	<.001	-.021	-.309	.758	+	.838	1.193
N2_LCOW	-.005	.005	-.082	-.954	.342	+	.526	1.901
N3_LMED	<.001	.012	-.003	-.039	.969	+	.739	1.354
N4_LSML	-.002	.002	-.091	-1.283	.201	+	.765	1.307
N5_LDFT	-.014	.027	-.040	-.510	.611	+	.622	1.608
N6_AGWK	-.246	.156	-.109	-1.580	.116		.810	1.235
P1_NBED	.598	.113	.381	5.297	<.001	+	.746	1.341
P2_ELEC	.021	.093	.017	.229	.819	+	.691	1.447
P3_CPBS	<.001	<.001	.064	.888	.376		.742	1.348
P4_CPAG	<.001	<.001	.055	.719	.473	+	.665	1.503
F1_LPDM	.138	.132	.083	1.052	.294	+	.624	1.601
F2_LPSC	<.001	<.001	.098	1.268	.206	+	.651	1.537
F3_TRDM	-.128	.150	-.066	-.856	.393		.642	1.557
F4_TRSC	<.001	<.001	.023	.299	.765	+	.667	1.498
F5_RTDM	-.714	.255	-.259	-2.801	.006	+	.452	2.212
F6_RTSC	<.001	<.001	.120	1.274	.204	+	.434	2.302
F7_PNDM	.078	.441	.017	.176	.861	+	.401	2.491
F8_PNSC	<.001	<.001	.041	.447	.655	+	.456	2.195
F9_CRDM	.095	.103	.071	.917	.360		.650	1.538
F10_CRSC	<.001	<.001	-.014	-.156	.876	+	.492	2.031

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Selecting only cases for which Region = Amazon

Model 1 – rural regional Amazon weighted

N = 203 Adjusted R^2 = .271 Std. Error of the Estimate = 7.628

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.421	.241		47.442	<.001			
H1_EDUL	.012	.029	.027	.415	.679	+	.857	1.167
H2_LITS	.182	.224	.059	.812	.418	+	.689	1.450
H3_FTRN	.097	.206	.032	.473	.637	+	.784	1.276
H4_HLTH	-.015	.011	-.091	-1.358	.176	-	.798	1.253
S1_TIME	-.142	.096	-.100	-1.484	.140	+	.799	1.252
N1_LOWN	<.001	<.001	.107	1.456	.147	+	.672	1.488
N1_LRNT	<.001	<.001	-.035	-.534	.594	+	.834	1.199
N2_LCOW	-.004	.005	-.071	-.842	.401	+	.501	1.996
N3_LMED	.006	.013	.035	.489	.626	+	.692	1.446
N4_LSML	-.003	.002	-.094	-1.364	.174	+	.752	1.330
N5_LDFT	-.032	.027	-.092	-1.186	.237	+	.595	1.680
N6_AGWK	-.435	.160	-.180	-2.722	.007		.824	1.214
P1_NBED	.645	.112	.423	5.767	<.001	+	.670	1.493
P2_ELEC	.059	.094	.047	.626	.532	+	.631	1.585
P3_CPBS	<.001	<.001	.029	.399	.690		.681	1.467
P4_CPAG	<.001	<.001	.091	1.187	.237	+	.612	1.635
F1_LPDM	.071	.130	.043	.549	.584	+	.598	1.671
F2_LPSC	<.001	<.001	.113	1.508	.133	+	.642	1.559
F3_TRDM	-.149	.147	-.075	-1.016	.311		.668	1.497
F4_TRSC	<.001	<.001	.011	.148	.882	+	.671	1.490
F5_RTDM	-.740	.236	-.283	-3.135	.002	+	.443	2.258
F6_RTSC	<.001	<.001	.148	1.620	.107	+	.432	2.316
F7_PNDM	.221	.484	.045	.457	.648	+	.371	2.698
F8_PNSC	<.001	<.001	.020	.218	.828	+	.411	2.434
F9_CRDM	.070	.101	.051	.691	.490		.657	1.523
F10_CRSC	<.001	<.001	-.054	-.620	.536	+	.479	2.086

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

c Selecting only cases for which Region = Amazon

Model 1 – global weighted without P1_NBED

N = 3872   Adjusted R^2 = .230   Std. Error of the Estimate = 12.4033868

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship	Collinearity Statistics	
	β	Std.Error	β				Tolerance	VIF
(Constant)	11.448	.069		166.701	<.001			
H1_EDUL	-.002	.008	-.005	-.315	.753	.951	1.051	
H2_LITS	.462	.057	.122	8.077	<.001	.872	1.147	
H3_FTRN	.481	.041	.172	11.640	<.001	.910	1.098	
H4_HLTH	<.001	.003	-.002	-.125	.900	.972	1.029	
S1_TIME	-.086	.029	-.042	-2.930	.003	.980	1.021	
N1_LOWN	<.001	<.001	.010	.441	.659	.408	2.451	
N1_LRNT	<.001	<.001	-.022	-1.557	.119	.986	1.015	
N2_LCOW	.003	.001	.040	1.798	.072	.409	2.447	
N3_LMED	-.004	.002	-.027	-1.707	.088	.793	1.262	
N4_LSML	-.003	.001	-.074	-4.806	<.001	.828	1.208	
N5_LDFT	-.038	.012	-.059	-3.212	.001	.593	1.685	
N6_AGWK	-.318	.043	-.110	-7.408	<.001	.903	1.108	
P1_NBED	.043	.041	.017	1.044	.297	.763	1.310	
P2_ELEC	<.001	<.001	.119	7.685	<.001	.831	1.203	
P3_CPBS	<.001	<.001	.010	.612	.540	.749	1.335	
P4_CPAG	.281	.026	.161	10.700	<.001	.883	1.132	
F1_LPDM	<.001	<.001	.033	2.256	.024	.929	1.077	
F2_LPSC	-.109	.025	-.068	-4.342	<.001	.820	1.219	
F3_TRDM	<.001	<.001	.068	4.354	<.001	.815	1.227	
F4_TRSC	.066	.046	.023	1.415	.157	.775	1.291	
F5_RTDM	<.001	<.001	.048	3.015	.003	.798	1.253	
F6_RTSC	-.104	.065	-.035	-1.596	.111	.412	2.425	
F7_PNDM	<.001	<.001	.057	2.582	.010	.410	2.439	
F8_PNSC	.103	.023	.069	4.574	<.001	.872	1.147	
F9_CRDM	<.001	<.001	.052	3.189	.001	.749	1.335	
F10_CRSC								

a Dependent Variable: Y1. Dependent variable ln total expenditure modified by economies of scale per household

b Weighted Least Squares Regression - Weighted by Factor of Expansion

Model 3 – district level variables only – mean consumption weighted

N = 55 Adjusted R^2 =.051 Std. Error of the Estimate = .28699

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship
	β	Std.Error	β			
(Constant)	12.049	.154		78.382	<.001	
NC1_DRY	-.031	.015	-.334	-2.080	.043	-
NC2_LAND	<.001	<.001	.028	.202	.841	+
NC3_SLP	-.017	.008	-.370	-2.146	.037	-
NC4_NVEG	.022	.016	.204	1.387	.172	+
PC1_ACC	<.001	<.001	-.126	-.811	.421	-

a Dependent Variable: Mean Ln Consumption (weighted)

Model 3 – district level variables only – median consumption weighted

N = 55 Adjusted R^2 =.034 Std. Error of the Estimate = .28643

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship
	β	Std.Error	β			
(Constant)	12.040	.153		78.473	<.001	
NC1_DRY	-.029	.015	-.321	-1.979	.053	-
NC2_LAND	<.001	<.001	<.001	-.001	.999	+
NC3_SLP	-.014	.008	-.310	-1.783	.081	-
NC4_NVEG	.019	.016	.181	1.224	.227	+
PC1_ACC	<.001	<.001	-.184	-1.176	.245	-

a Dependent Variable: Median Ln Cosumption (weighted)

Model 3 – district level variables only – mean consumption weighted – rural areas

N =31 Adjusted R^2 =.033 Std. Error of the Estimate = .23209

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship
	β	Std.Error	β			
(Constant)	11.812	.145		81.355	<.001	
NC1_DRY	-.022	.015	-.292	-1.450	.159	-
NC2_LAND	<.001	<.001	.146	.784	.440	+
NC3_SLP	-.014	.009	-.323	-1.621	.118	-
NC4_NVEG	-.005	.019	-.050	-.249	.805	+
PC1_ACC	<.001	<.001	.028	.136	.893	-

a Dependent Variable: Rural mean ln consumption (weighted)

Model 3 – district level variables only – mean consumption weighted – urban areas

N = 32 Adjusted R^2 = 0.133 Std. Error of the Estimate = 0.19257

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Expected Relationship
	β	Std.Error	β			
(Constant)	12.180	.156		77.897	<.001	
NC1_DRY	-.028	.015	-.474	-1.892	.070	-
NC2_LAND	<.001	<.001	.179	.993	.330	+
NC3_SLP	-.017	.007	-.605	-2.350	.027	-
NC4_NVEG	.023	.014	.328	1.631	.115	+
PC1_ACC	<.001	<.001	-.113	-.510	.614	-

a Dependent Variable: Mean ln consumption for urban households

Model 4 – district and household level variables – mean consumption weighted

N = 55 Adjusted $R^2 = 0.738$ Std. Error of the Estimate = 0.15076

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
	β	Std.Error	β			Tolerance	VIF
(Constant)	11.254	.459		24.508	<.001		
NC1_DRY	-.023	.009	-.248	-2.574	.014	.521	1.920
NC2_LAND	<.001	<.001	.102	1.078	.288	.540	1.852
NC3_SLP	-.027	.005	-.602	-5.897	<.001	.465	2.152
NC4_NVEG	.007	.009	.063	.739	.464	.667	1.498
PC1_ACC	<.001	<.001	.005	.039	.969	.314	3.180
HC1_EDUL	-.106	.093	-.100	-1.149	.258	.643	1.555
HC2_LITS	1.453	.377	.418	3.855	<.001	.412	2.427
HC3_FTRN	1.321	.499	.319	2.647	.012	.334	2.995
NC1_LOWN	<.001	<.001	-.118	-.885	.381	.271	3.689
NC1_LRNT	<.001	<.001	.186	1.759	.086	.434	2.305
N2_LCOW	.023	.017	.218	1.379	.176	.193	5.178
NC3_LMED	-.014	.013	-.146	-1.143	.260	.298	3.351
NC4_LSML	-.001	.004	-.036	-.280	.781	.290	3.443
NC5_LDFT	.004	.102	.007	.037	.971	.150	6.681
NC6_AGWK	-.875	.287	-.344	-3.047	.004	.381	2.625

a Dependent Variable: Mean Ln Consumption (weighted)

Model 4 – district and household level variables – median consumption weighted

N = 55 Adjusted R^2 = 0.692 Std. Error of the Estimate = 0.16163

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
	β	Std.Error	β			Tolerance	VIF
(Constant)	11.430	.492		23.217	<.001		
NC1_DRY	-.023	.009	-.254	-2.430	.020	.521	1.920
NC2_LAND	<.001	<.001	.083	.808	.424	.540	1.852
NC3_SLP	-.023	.005	-.510	-4.611	<.001	.465	2.152
NC4_NVEG	.004	.010	.033	.362	.719	.667	1.498
PC1_ACC	<.001	<.001	-.097	-.720	.476	.314	3.180
HC1_EDUL	-.148	.099	-.140	-1.490	.144	.643	1.555
HC2_LITS	1.432	.404	.417	3.543	.001	.412	2.427
HC3_FTRN	1.477	.535	.361	2.761	.009	.334	2.995
NC1_LOWN	<.001	<.001	-.075	-.516	.609	.271	3.689
NC1_LRNT	<.001	<.001	.221	1.928	.061	.434	2.305
N2_LCOW	.024	.018	.228	1.328	.192	.193	5.178
NC3_LMED	-.001	.013	-.006	-.044	.965	.298	3.351
NC4_LSML	-.005	.005	-.144	-1.028	.310	.290	3.443
NC5_LDFT	-.006	.110	-.010	-.052	.959	.150	6.681
NC6_AGWK	-.789	.308	-.313	-2.563	.014	.381	2.625

a Dependent Variable: Median Ln Cosumption (weighted)

Model 4 – district and household level variables – mean consumption weighted – rural areas

N = 31 Adjusted R^2 = 0.460 Std. Error of the Estimate = 0.17350

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
	β	Std.Error	β			Tolerance	VIF
(Constant)	11.006	.867		12.693	<.001		
NC1_DRY	-.006	.015	-.082	-.427	.675	.491	2.037
NC2_LAND	<.001	<.001	.039	.166	.870	.329	3.040
NC3_SLP	-.028	.009	-.647	-3.127	.007	.421	2.375
NC4_NVEG	-.004	.018	-.039	-.211	.836	.513	1.951
PC1_ACC	<.001	.001	-.184	-.643	.530	.221	4.535
HC1_EDUL	-.007	.228	-.008	-.032	.975	.298	3.356
HC2_LITS	1.158	.614	.443	1.886	.079	.326	3.070
HC3_FTRN	1.851	1.324	.272	1.398	.182	.476	2.102
NC1_LOWN	<.001	<.001	-.167	-.684	.504	.301	3.319
NC1_LRNT	<.001	<.001	.192	.883	.391	.380	2.633
N2_LCOW	.042	.023	.543	1.834	.087	.205	4.873
NC3_LMED	-.009	.016	-.143	-.563	.582	.278	3.599
NC4_LSML	.001	.007	.021	.093	.927	.370	2.703
NC5_LDFT	-.051	.143	-.106	-.353	.729	.199	5.020
NC6_AGWK	-.665	.388	-.346	-1.715	.107	.441	2.265

a Dependent Variable: Rural mean ln consumption (weighted)

Model 4 – district and household level variables – mean consumption weighted – urban areas

N = 32 Adjusted $R^2 = 0.270$ Std. Error of the Estimate = 0.17678

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
	β	Std.Error	β			Tolerance	VIF
(Constant)	9.020	1.881		4.795	<.001		
NC1_DRY	-.032	.016	-.539	-	.067	.314	3.189
NC2_LAND	<.001	<.001	.042	.166	.870	.366	2.731
NC3_SLP	-.023	.007	-.783	-	.008	.356	2.807
NC4_NVEG	.008	.016	.112	.501	.624	.468	2.138
PC1_ACC	<.001	.001	.044	.147	.885	.265	3.778
HC1_EDUL	.057	.141	.081	.404	.692	.590	1.696
HC2_LITS	3.292	1.937	.489	1.700	.109	.285	3.512
HC3_FTRN	.121	.803	.040	.150	.882	.336	2.978
NC1_LOWN	<.001	<.001	.066	.173	.865	.162	6.157
NC1_LRNT	<.001	<.001	-.339	-	.136	.504	1.986
N2_LCOW	-.011	.056	-.114	-.202	.843	.074	13.491
NC3_LMED	.140	.211	.281	.660	.518	.130	7.674
NC4_LSML	<.001	.010	-.003	-.011	.992	.366	2.729
NC5_LDFT	-.025	.609	-.024	-.040	.968	.066	15.241
NC6_AGWK	-	1.148	-.239	-	.299	.474	2.108

a Dependent Variable: Mean ln consumption for urban households

Model 5 – multilevel model global intercept only

$$\mathrm{y1}_{ij} = \beta_{0j} + e_{ij}$$
$$\beta_{0j} = 11.779(0.039) + u_{0j}$$

$$u_{0j} \sim \mathrm{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.078(0.016)$$
$$e_{ij} \sim \mathrm{N}(0,\ \sigma^2_{e}) \quad \sigma^2_{e} = 0.448(0.008)$$
$$\textit{-2*loglikelihood} = 11620.710(5641 \text{ of } 5810 \text{ cases in use})$$

Model 5 – multilevel model urban areas weighted intercept only

$$\mathrm{y1}_{ij} = \beta_{0j} + e_{ij}$$
$$\beta_{0j} = 11.986(0.037) + u_{0j}$$

$$u_{0j} \sim \mathrm{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.035(0.009)$$
$$e_{ij} \sim \mathrm{N}(0,\ \sigma^2_{e}) \quad \sigma^2_{e} = 0.439(0.030)$$
$$\textit{-2*loglikelihood} = 6512.918(3210 \text{ of } 3278 \text{ cases in use})$$

Model 5 – multilevel model rural areas weighted intercept only

$$\mathrm{y1}_{ij} = \beta_{0j} + e_{ij}$$
$$\beta_{0j} = 11.603(0.042) + u_{0j}$$

$$u_{0j} \sim \mathrm{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.048(0.012)$$
$$e_{ij} \sim \mathrm{N}(0,\ \sigma^2_{e}) \quad \sigma^2_{e} = 0.423(0.022)$$
$$\textit{-2*loglikelihood} = 4910.320(2431 \text{ of } 2532 \text{ cases in use})$$

Model 5 – multilevel model urban areas weighted household level variables

$$\begin{aligned} \text{y1}_{ij} = \beta_{0j} &+ 0.009(0.007)\text{h1\_edul}_{ij} + 0.243(0.105)\text{h2\_lits}_{ij} + 0.302(0.037)\text{h3\_ftrn}_{ij} + -0.001(0.003)\text{h4\_hlth}_{ij} + \\ &-0.068(0.025)\text{s1\_time}_{ij} + 0.000(0.000)\text{n1\_lown}_{ij} + 0.000(0.000)\text{n1\_lrnt}_{ij} + 0.006(0.003)\text{n2\_lcow}_{ij} + \\ &-0.005(0.007)\text{n3\_lmed}_{ij} + 0.000(0.001)\text{n4\_lsml}_{ij} + 0.000(0.026)\text{n5\_ldft}_{ij} + -0.038(0.135)\text{n6\_agwk}_{ij} + \\ &0.482(0.034)\text{p1\_nbed}_{ij} + 0.239(0.117)\text{p2\_elec}_{ij} + 0.000(0.000)\text{p3\_cpbs}_{ij} + 0.000(0.000)\text{p4\_agcp}_{ij} + \\ &0.228(0.036)\text{f1\_lpdm}_{ij} + 0.000(0.000)\text{f2\_lpsc}_{ij} + -0.089(0.025)\text{f3\_rtdm}_{ij} + 0.000(0.000)\text{f4\_trsc}_{ij} + \\ &-0.024(0.040)\text{f5\_rtdm}_{ij} + 0.000(0.000)\text{f6\_rtsc}_{ij} + -0.160(0.060)\text{f7\_pndm}_{ij} + 0.000(0.000)\text{f8\_pnsc}_{ij} + \\ &0.128(0.023)\text{f9\_crdm}_{ij} + 0.000(0.000)\text{f10\_crsc}_{ij} + e_{ij} \end{aligned}$$

$$\beta_{0j} = 11.080(0.134) + u_{0j}$$

$$u_{0j} \sim \text{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.028(0.008)$$

$$e_{ij} \sim \text{N}(0,\ \sigma^2_{e}) \quad \sigma^2_{e} = 0.297(0.019)$$

$$-2{*}loglikelihood = 3623.491(2215 \text{ of } 3278 \text{ cases in use})$$

Model 5 – multilevel model rural areas weighted household level variables

$$\begin{aligned} \text{y1}_{ij} = \beta_{0j} &+ -0.015(0.014)\text{h1\_edul}_{ij} + 0.361(0.074)\text{h2\_lits}_{ij} + 0.347(0.095)\text{h3\_ftrn}_{ij} + 0.002(0.005)\text{h4\_hlth}_{ij} + \\ &-0.114(0.051)\text{s1\_time}_{ij} + 0.000(0.000)\text{n1\_lown}_{ij} + 0.000(0.000)\text{n1\_lrnt}_{ij} + -0.001(0.002)\text{n2\_lcow}_{ij} + \\ &0.001(0.002)\text{n3\_nmed}_{ij} + -0.001(0.001)\text{n4\_lsml}_{ij} + -0.028(0.008)\text{n5\_ldft}_{ij} + -0.170(0.043)\text{n6\_agwk}_{ij} + \\ &0.503(0.053)\text{p1\_nbed}_{ij} + -0.069(0.059)\text{p2\_elec}_{ij} + 0.000(0.000)\text{p3\_cpbs}_{ij} + 0.000(0.000)\text{p4\_agcp}_{ij} + \\ &0.214(0.031)\text{f1\_lpdm}_{ij} + 0.000(0.000)\text{f2\_lpsc}_{ij} + -0.177(0.044)\text{f3\_trdm}_{ij} + 0.000(0.000)\text{f4\_trsc}_{ij} + \\ &-0.005(0.081)\text{f5\_rtdm}_{ij} + 0.000(0.000)\text{f6\_rtsc}_{ij} + 0.055(0.148)\text{f7\_pndm}_{ij} + 0.000(0.000)\text{f8\_pnsc}_{ij} + \\ &0.093(0.030)\text{f9\_crdm}_{ij} + 0.000(0.000)\text{f10\_crsc}_{ij} + e_{ij} \end{aligned}$$

$$\beta_{0j} = 11.273(0.092) + u_{0j}$$

$$u_{0j} \sim \text{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.025(0.008)$$

$$e_{ij} \sim \text{N}(0,\ \sigma^2_{e}) \quad \sigma^2_{e} = 0.327(0.021)$$

$$-2{*}loglikelihood = 2960.778(1657 \text{ of } 2532 \text{ cases in use})$$

Model 5 – multilevel model urban areas weighted household level variables zscore

$$\begin{aligned}
\text{y1}_{ij} = {} & \beta_{0j} + 0.012(0.010)\text{h1_edul_z}_{ij} + 0.057(0.025)\text{h2_lits_z}_{ij} + 0.074(0.009)\text{h3_ftrn_z}_{ij} + -0.005(0.013)\text{h4_hlth_z}_{ij} + \\
& -0.023(0.009)\text{s1_time_z}_{ij} + -0.062(0.011)\text{n1_lown_z}_{ij} + -0.031(0.032)\text{n1_lrnt_z}_{ij} + 0.066(0.027)\text{n2_lcow_z}_{ij} + \\
& -0.027(0.034)\text{n3_lmed_z}_{ij} + -0.011(0.021)\text{n4_lsml_z}_{ij} + 0.000(0.035)\text{n5_ldft_z}_{ij} + -0.010(0.034)\text{n6_agwk_z}_{ij} + \\
& 0.202(0.014)\text{p1_nbed_z}_{ij} + 0.077(0.038)\text{p2_elec_z}_{ij} + 0.072(0.015)\text{p3_cpbs_z}_{ij} + 0.046(0.044)\text{p4_agcp_z}_{ij} + \\
& 0.095(0.015)\text{f1_lpdm_z}_{ij} + 0.019(0.012)\text{f2_lpsc_z}_{ij} + -0.039(0.011)\text{f3_trdm}_{ij} + 0.021(0.012)\text{f4_trsc_ln}_{ij} + \\
& -0.006(0.011)\text{f5_rtdm_z}_{ij} + 0.026(0.008)\text{f6_rtsc_z}_{ij} + -0.041(0.016)\text{f7_pndm_z}_{ij} + 0.026(0.012)\text{f8_pnsc_z}_{ij} + \\
& 0.059(0.011)\text{f9_crdm_z}_{ij} + 0.021(0.007)\text{f10_crsc_z}_{ij} + e_{ij}
\end{aligned}$$

$$\beta_{0j} = 11.882(0.033) + u_{0j}$$

$$u_{0j} \sim \text{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.028(0.008)$$

$$e_{ij} \sim \text{N}(0,\ \sigma^2_{e}) \quad \sigma^2_{e} = 0.297(0.019)$$

*-2*loglikelihood* = 3623.491(2215 of 3278 cases in use)

Model 5 – multilevel model rural areas weighted household level variables zscore

$$\begin{aligned}
\text{y1}_{ij} = {} & \beta_{0j} + -0.020(0.019)\text{h1_edul_z}_{ij} + 0.085(0.018)\text{h2_lits_z}_{ij} + 0.085(0.023)\text{h3_ftrn_z}_{ij} + 0.009(0.021)\text{h4_hlth_z}_{ij} + \\
& -0.039(0.018)\text{s1_time_z}_{ij} + 0.044(0.019)\text{n1_lown_z}_{ij} + -0.004(0.009)\text{n1_lrnt_z}_{ij} + -0.007(0.017)\text{n2_lcow_z}_{ij} + \\
& 0.004(0.012)\text{n3_lmed_z}_{ij} + -0.028(0.013)\text{n4_lsml_z}_{ij} + -0.037(0.011)\text{n5_ldft_z}_{ij} + -0.042(0.011)\text{n6_agwk_z}_{ij} + \\
& 0.211(0.022)\text{p1_nbed_z}_{ij} + -0.022(0.019)\text{p2_elec_z}_{ij} + 0.129(0.078)\text{p3_cpbs_z}_{ij} + 0.028(0.030)\text{p4_agcp_z}_{ij} + \\
& 0.089(0.013)\text{f1_lpdm_z}_{ij} + 0.003(0.004)\text{f2_lpsc_z}_{ij} + -0.078(0.020)\text{f3_trdm}_{ij} + 0.165(0.040)\text{f4_trsc_ln}_{ij} + \\
& -0.001(0.021)\text{f5_rtdm_z}_{ij} + 0.068(0.047)\text{f6_rtsc_z}_{ij} + 0.014(0.038)\text{f7_pndm_z}_{ij} + 0.005(0.052)\text{f8_pnsc_z}_{ij} + \\
& 0.043(0.014)\text{f9_crdm_z}_{ij} + 0.025(0.024)\text{f10_crsc_z}_{ij} + e_{ij}
\end{aligned}$$

$$\beta_{0j} = 11.794(0.036) + u_{0j}$$

$$u_{0j} \sim \text{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.025(0.008)$$

$$e_{ij} \sim \text{N}(0,\ \sigma^2_{e}) \quad \sigma^2_{e} = 0.327(0.021)$$

*-2*loglikelihood* = 2960.778(1657 of 2532 cases in use)

Model 5 – multilevel model urban areas weighted household level variables zscore random effects

$$\begin{aligned}
\mathrm{y1}_{ij} &= \beta_{0j} + 0.012(0.010)\mathrm{h1_edul_z}_{ij} + 0.057(0.025)\mathrm{h2_lits_z}_{ij} + 0.074(0.009)\mathrm{h3_ftrn_z}_{ij} + -0.005(0.013)\mathrm{h4_hlth_z}_{ij} + \\
&\quad -0.023(0.009)\mathrm{s1_time_z}_{ij} + -0.062(0.011)\mathrm{n1_lown_z}_{ij} + -0.031(0.032)\mathrm{n1_lrnt_z}_{ij} + 0.066(0.027)\mathrm{n2_lcow_z}_{ij} + \\
&\quad -0.027(0.034)\mathrm{n3_lmed_z}_{ij} + -0.011(0.021)\mathrm{n4_lsml_z}_{ij} + 0.000(0.035)\mathrm{n5_ldft_z}_{ij} + -0.010(0.034)\mathrm{n6_agwk_z}_{ij} + \\
&\quad 0.202(0.014)\mathrm{p1_nbed_z}_{ij} + 0.077(0.038)\mathrm{p2_elec_z}_{ij} + 0.072(0.015)\mathrm{p3_cpbs_z}_{ij} + 0.046(0.044)\mathrm{p4_agcp_z}_{ij} + \\
&\quad 0.095(0.015)\mathrm{f1_lpdm_z}_{ij} + 0.019(0.012)\mathrm{f2_lpsc_z}_{ij} + -0.039(0.011)\mathrm{f3_trdm}_{ij} + 0.021(0.012)\mathrm{f4_trsc_ln}_{ij} + \\
&\quad -0.006(0.011)\mathrm{f5_rtdm_z}_{ij} + 0.026(0.008)\mathrm{f6_rtsc_z}_{ij} + -0.041(0.016)\mathrm{f7_pndm_z}_{ij} + 0.026(0.012)\mathrm{f8_pnsc_z}_{ij} + \\
&\quad 0.059(0.011)\mathrm{f9_crdm_z}_{ij} + 0.021(0.007)\mathrm{f10_crsc_z}_{ij} + e_{ij} \\
\beta_{0j} &= 11.882(0.033) + u_{0j}
\end{aligned}$$

$$u_{0j} \sim \mathrm{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.028(0.008)$$
$$e_{ij} \sim \mathrm{N}(0,\ \sigma^2_e) \quad \sigma^2_e = 0.297(0.019)$$
$$\textit{-2*loglikelihood} = 3623.491(2215 \text{ of } 3278 \text{ cases in use})$$

Model 5 – multilevel model rural areas weighted household level variables zscore random effects

$$\begin{aligned}
\mathrm{y1}_{ij} &= \beta_{0j} + -0.022(0.018)\mathrm{h1_edul_z}_{ij} + 0.085(0.017)\mathrm{h2_lits_z}_{ij} + 0.083(0.022)\mathrm{h3_ftrn_z}_{ij} + 0.007(0.020)\mathrm{h4_hlth_z}_{ij} + \\
&\quad -0.040(0.017)\mathrm{s1_time_z}_{ij} + 0.047(0.019)\mathrm{n1_lown_z}_{ij} + -0.003(0.008)\mathrm{n1_lrnt_z}_{ij} + -0.010(0.016)\mathrm{n2_lcow_z}_{ij} + \\
&\quad 0.009(0.012)\mathrm{n3_lmed_z}_{ij} + -0.028(0.013)\mathrm{n4_lsml_z}_{ij} + -0.029(0.010)\mathrm{n5_ldft_z}_{ij} + -0.041(0.011)\mathrm{n6_agwk_z}_{ij} + \\
&\quad 0.208(0.022)\mathrm{p1_nbed_z}_{ij} + \beta_{14j}\mathrm{p2_elec_z}_{ij} + \beta_{15j}\mathrm{p3_cpbs_z}_{ij} + 0.009(0.033)\mathrm{p4_agcp_z}_{ij} + 0.091(0.013)\mathrm{f1_lpdm_z}_{ij} + \\
&\quad 0.003(0.004)\mathrm{f2_lpsc_z}_{ij} + -0.079(0.020)\mathrm{f3_trdm}_{ij} + 0.167(0.040)\mathrm{f4_trsc_ln}_{ij} + -0.012(0.020)\mathrm{f5_rtdm_z}_{ij} + \\
&\quad 0.068(0.048)\mathrm{f6_rtsc_z}_{ij} + 0.014(0.037)\mathrm{f7_pndm_z}_{ij} + 0.004(0.053)\mathrm{f8_pnsc_z}_{ij} + 0.043(0.013)\mathrm{f9_crdm_z}_{ij} + \\
&\quad 0.020(0.022)\mathrm{f10_crsc_z}_{ij} + e_{ij} \\
\beta_{0j} &= 11.834(0.031) + u_{0j} \\
\beta_{14j} &= -0.022(0.019) + u_{14j} \\
\beta_{15j} &= 0.425(0.117) + u_{15j}
\end{aligned}$$

$$\begin{bmatrix} u_{0j} \\ u_{14j} \\ u_{15j} \end{bmatrix} \sim \mathrm{N}(0,\ \Omega_u) \ : \ \Omega_u = \begin{bmatrix} 0.014(0.007) & & \\ -0.002(0.003) & 0.004(0.002) & \\ -0.019(0.023) & 0.003(0.009) & 0.124(0.049) \end{bmatrix}$$

$$e_{ij} \sim \mathrm{N}(0,\ \sigma^2_e) \quad \sigma^2_e = 0.317(0.020)$$
$$\textit{-2*loglikelihood} = 2941.914(1657 \text{ of } 2532 \text{ cases in use})$$

Model 5 – multilevel model urban areas weighted 2 level variables zscore random effects

$$\begin{aligned}
\text{y1}_{ij} = {} & \beta_{0j} + 0.013(0.010)\text{h1_edul_z}_{ij} + 0.058(0.025)\text{h2_lits_z}_{ij} + 0.074(0.009)\text{h3_ftrn_z}_{ij} + -0.005(0.013)\text{h4_hlth_z}_{ij} + \\
& -0.023(0.009)\text{s1_time_z}_{ij} + -0.063(0.011)\text{n1_lown_z}_{ij} + -0.037(0.032)\text{n1_lrnt_z}_{ij} + 0.067(0.028)\text{n2_lcow_z}_{ij} + \\
& -0.030(0.034)\text{n3_lmed_z}_{ij} + -0.009(0.022)\text{n4_lsml_z}_{ij} + 0.002(0.035)\text{n5_ldft_z}_{ij} + -0.013(0.033)\text{n6_agwk_z}_{ij} + \\
& 0.204(0.014)\text{p1_nbed_z}_{ij} + 0.074(0.040)\text{p2_elec_z}_{ij} + 0.073(0.015)\text{p3_cpbs_z}_{ij} + 0.046(0.045)\text{p4_agcp_z}_{ij} + \\
& 0.096(0.015)\text{f1_lpdm_z}_{ij} + 0.019(0.012)\text{f2_lpsc_z}_{ij} + -0.040(0.011)\text{f3_trdm}_{ij} + 0.022(0.012)\text{f4_trsc_ln}_{ij} + \\
& -0.006(0.011)\text{f5_rtdm_z}_{ij} + 0.026(0.008)\text{f6_rtsc_z}_{ij} + -0.041(0.016)\text{f7_pndm_z}_{ij} + 0.026(0.012)\text{f8_pnsc_z}_{ij} + \\
& 0.060(0.011)\text{f9_crdm_z}_{ij} + 0.021(0.007)\text{f10_crsc_z}_{ij} + -0.088(0.037)\text{NC1_DRY_z} + 0.018(0.029)\text{NC2_LAND_z} + \\
& -0.132(0.030)\text{NC3_SLP_z} + 0.094(0.028)\text{NC4_NVEG_z} + -0.048(0.032)\text{PC1_ACC_z} + e_{ij}
\end{aligned}$$

$$\beta_{0j} = 11.899(0.032) + u_{0j}$$

$$u_{0j} \sim \text{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.012(0.006)$$

$$e_{ij} \sim \text{N}(0,\ \sigma^2_e) \quad \sigma^2_e = 0.296(0.019)$$

$$\textit{-2*loglikelihood} = 3601.073(2215 \text{ of } 3278 \text{ cases in use})$$

Model 5 – multilevel model rural areas weighted 2 level variables zscore random effects

$$\begin{aligned}
\text{y1}_{ij} = {} & \beta_{0j} + -0.022(0.018)\text{h1_edul_z}_{ij} + 0.086(0.017)\text{h2_lits_z}_{ij} + 0.084(0.023)\text{h3_ftrn_z}_{ij} + 0.006(0.020)\text{h4_hlth_z}_{ij} + \\
& -0.039(0.018)\text{s1_time_z}_{ij} + 0.045(0.019)\text{n1_lown_z}_{ij} + -0.003(0.008)\text{n1_lrnt_z}_{ij} + -0.009(0.016)\text{n2_lcow_z}_{ij} + \\
& 0.007(0.013)\text{n3_lmed_z}_{ij} + -0.026(0.013)\text{n4_lsml_z}_{ij} + -0.029(0.010)\text{n5_ldft_z}_{ij} + -0.043(0.010)\text{n6_agwk_z}_{ij} + \\
& 0.209(0.022)\text{p1_nbed_z}_{ij} + \beta_{14j}\text{p2_elec_z}_{ij} + \beta_{15j}\text{p3_cpbs_z}_{ij} + 0.009(0.033)\text{p4_agcp_z}_{ij} + 0.090(0.013)\text{f1_lpdm_z}_{ij} + \\
& 0.003(0.004)\text{f2_lpsc_z}_{ij} + -0.079(0.019)\text{f3_trdm}_{ij} + 0.171(0.039)\text{f4_trsc_ln}_{ij} + -0.015(0.021)\text{f5_rtdm_z}_{ij} + \\
& 0.070(0.048)\text{f6_rtsc_z}_{ij} + 0.012(0.036)\text{f7_pndm_z}_{ij} + 0.005(0.053)\text{f8_pnsc_z}_{ij} + 0.044(0.013)\text{f9_crdm_z}_{ij} + \\
& 0.023(0.023)\text{f10_crsc_z}_{ij} + -0.033(0.029)\text{NC1_DRY_z}_j + 0.011(0.023)\text{NC2_LAND_z}_j + -0.094(0.032)\text{NC3_SLP_z}_j + \\
& -0.022(0.033)\text{NC4_NVEG_z}_j + -0.003(0.023)\text{PC1_ACC_z}_j + e_{ij}
\end{aligned}$$

$$\beta_{0j} = 11.844(0.030) + u_{0j}$$

$$\beta_{14j} = -0.022(0.019) + u_{14j}$$

$$\beta_{15j} = 0.422(0.121) + u_{15j}$$

$$\begin{bmatrix} u_{0j} \\ u_{14j} \\ u_{15j} \end{bmatrix} \sim \text{N}(0,\ \Omega_u) : \Omega_u = \begin{bmatrix} 0.008(0.003) & & \\ 0.001(0.003) & 0.005(0.002) & \\ -0.013(0.014) & 0.002(0.008) & 0.108(0.041) \end{bmatrix}$$

$$e_{ij} \sim \text{N}(0,\ \sigma^2_e) \quad \sigma^2_e = 0.316(0.020)$$

$$\textit{-2*loglikelihood} = 2931.787(1657 \text{ of } 2532 \text{ cases in use})$$

Model 5 – multilevel model urban areas weighted interactions zscore random effects

$$
\begin{aligned}
\text{y1}_{ij} = {} & \beta_{0j} + 0.013(0.010)\text{h1\_edul\_z}_{ij} + 0.056(0.025)\text{h2\_lits\_z}_{ij} + 0.073(0.010)\text{h3\_ftrn\_z}_{ij} + -0.004(0.013)\text{h4\_hlth\_z}_{ij} + \\
& -0.022(0.009)\text{s1\_time\_z}_{ij} + -0.068(0.010)\text{n1\_lown\_z}_{ij} + -0.042(0.032)\text{n1\_lrnt\_z}_{ij} + 0.069(0.028)\text{n2\_lcow\_z}_{ij} + \\
& -0.038(0.033)\text{n3\_lmed\_z}_{ij} + -0.010(0.022)\text{n4\_lsml\_z}_{ij} + 0.006(0.034)\text{n5\_ldft\_z}_{ij} + -0.011(0.033)\text{n6\_agwk\_z}_{ij} + \\
& 0.205(0.014)\text{p1\_nbed\_z}_{ij} + 0.073(0.040)\text{p2\_elec\_z}_{ij} + 0.083(0.013)\text{p3\_cpbs\_z}_{ij} + 0.047(0.041)\text{p4\_agcp\_z}_{ij} + \\
& 0.097(0.015)\text{f1\_lpdm\_z}_{ij} + 0.020(0.012)\text{f2\_lpsc\_z}_{ij} + -0.039(0.010)\text{f3\_trdm}_{ij} + 0.020(0.012)\text{f4\_trsc\_ln}_{ij} + \\
& 0.005(0.010)\text{f5\_rtdm\_z}_{ij} + 0.022(0.007)\text{f6\_rtsc\_z}_{ij} + -0.041(0.016)\text{f7\_pndm\_z}_{ij} + 0.026(0.012)\text{f8\_pnsc\_z}_{ij} + \\
& 0.060(0.011)\text{f9\_crdm\_z}_{ij} + 0.017(0.007)\text{f10\_crsc\_z}_{ij} + -0.091(0.036)\text{NC1\_DRY\_z} + 0.018(0.029)\text{NC2\_LAND\_z} + \\
& -0.135(0.029)\text{NC3\_SLP\_z} + 0.098(0.028)\text{NC4\_NVEG\_z} + -0.049(0.031)\text{PC1\_ACC\_z} + \\
& 0.028(0.007)\text{f5\_rtdm\_z.NC1\_DRY\_z}_{ij} + -0.022(0.013)\text{p3\_cpbs\_z.NC1\_DRY\_z}_{ij} + e_{ij} \\
\beta_{0j} = {} & 11.902(0.032) + u_{0j}
\end{aligned}
$$

$$
\begin{aligned}
& u_{0j} \sim \text{N}(0,\ \sigma^2_{u0}) \quad \sigma^2_{u0} = 0.012(0.006) \\
& e_{ij} \sim \text{N}(0,\ \sigma^2_{e}) \quad \sigma^2_{e} = 0.295(0.019) \\
& -2{*}loglikelihood = 3589.044 (2215 \text{ of } 3278 \text{ cases in use})
\end{aligned}
$$

Coefficients, standard errors and significance for urban households

	Expected Relationship	Coefficient (Std Error)	t
H1_EDUL_Z	+	0.013 (0.010)	1.3
H2_LITS_Z	+	0.056 (0.025)	2.24 *
H3_FTRN_Z	+	0.073 (0.010)	7.3***
H4_HLTH_Z	-	-0.004 (0.013)	-0.308
S1_TIME_Z	+	-0.022 (0.009)	-2.444 *
N1_LOWN_Z	+	-0.068 (0.010)	-6.8***
N1_LRNT_Z	+	-0.042 (0.032)	-1.313
N2_LCOW_Z	+	0.069 (0.028)	2.464 *
N3_LMED_Z	+	-0.038 (0.033)	-1.152
N4_LSML_Z	+	-0.010 (0.022)	-0.455
N5_LDFT_Z	+	0.006 (0.034)	0.176
N6_AGWK_Z		-0.011 (0.033)	-0.333
P1_NBED_Z	+	0.205 (0.014)	14.643***
P2_ELEC_Z	+	0.073 (0.040)	1.825
P3_CPBS_Z	+	0.083 (0.013)	6.385***
P4_CPAG_Z	+	0.047 (0.041)	1.146
F1_LPDM_Z	+	0.097 (0.015)	6.467***
F2_LPSC_Z	+	0.020 (0.012)	1.667

F3_TRDM_Z		-0.039 (0.010)	-3.9***
F4_TRSC_Z	+	0.020 (0.012)	1.667
F5_RTDM_Z	+	0.005 (0.010)	0.5
F6_RTSC_Z	+	0.022 (0.007)	3.143***
F7_PNDM_Z	+	-0.041 (0.016)	-2.563 *
F8_PNSC_Z	+	0.026 (0.012)	2.167 *
F9_CRDM_Z		0.060 (0.011)	5.455***
F10_CRSC_Z	+	0.017 (0.007)	2.429 **
NC1_DRY_Z	-	-0.091 (0.036)	-2.528 *
NC2_LAND_Z	+	0.018 (0.029)	0.621
NC3_SLP_Z	-	-0.135 (0.029)	-4.655***
NC4_NVEG_Z	+	0.098 (0.028)	3.5***
PC1_ACC_Z	-	-0.049 (0.031)	-1.581
P3_CPBS_Z*NC1_DRY_Z		-0.022 (0.013)	-1.692
F5_RTDM_Z*NC1_DRY_Z		0.028 (0.007)	4***

* Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9% level

Model 5 – multilevel model rural areas weighted interactions zscore random effects

$$\begin{aligned}
\text{y1}_{ij} = {} & \beta_{0j} + -0.021(0.018)\text{h1_edul_z}_{ij} + 0.087(0.017)\text{h2_lits_z}_{ij} + 0.085(0.024)\text{h3_ftrn_z}_{ij} + 0.009(0.020)\text{h4_hlth_z}_{ij} + \\
& -0.039(0.017)\text{s1_time_z}_{ij} + 0.045(0.018)\text{n1_lown_z}_{ij} + -0.002(0.009)\text{n1_lrnt_z}_{ij} + -0.010(0.015)\text{n2_lcow_z}_{ij} + \\
& 0.007(0.012)\text{n3_lmed_z}_{ij} + -0.026(0.013)\text{n4_lsml_z}_{ij} + -0.028(0.010)\text{n5_ldft_z}_{ij} + -0.044(0.010)\text{n6_agwk_z}_{ij} + \\
& 0.205(0.017)\text{p1_nbed_z}_{ij} + \beta_{14j}\text{p2_elec_z}_{ij} + \beta_{15j}\text{p3_cpbs_z}_{ij} + 0.015(0.029)\text{p4_agcp_z}_{ij} + 0.089(0.014)\text{f1_lpdm_z}_{ij} + \\
& 0.003(0.004)\text{f2_lpsc_z}_{ij} + -0.073(0.019)\text{f3_trdm_z}_{ij} + 0.133(0.040)\text{f4_trsc_z}_{ij} + -0.008(0.020)\text{f5_rtdm_z}_{ij} + \\
& 0.052(0.045)\text{f6_rtsc_z}_{ij} + 0.008(0.037)\text{f7_pndm_z}_{ij} + 0.004(0.056)\text{f8_pnsc_z}_{ij} + 0.044(0.012)\text{f9_crdm_z}_{ij} + \\
& -0.043(0.031)\text{f10_crsc_z}_{ij} + -0.031(0.028)\text{NC1_DRY_z}_{j} + 0.007(0.021)\text{NC2_LAND_z}_{j} + -0.071(0.032)\text{NC3_SLP_z}_{j} + \\
& -0.010(0.030)\text{NC4_NVEG_z}_{j} + -0.007(0.021)\text{PC1_ACC_z}_{j} + 0.102(0.040)\text{NC3_SLP_z.f10_crsc_z}_{ij} + \\
& 0.043(0.013)\text{p1_nbed_z.NC3_SLP_z}_{ij} + 0.072(0.043)\text{f4_trsc_z.NC3_SLP_z}_{ij} + e_{ij}
\end{aligned}$$

$$\beta_{0j} = 11.831(0.030) + u_{0j}$$
$$\beta_{14j} = -0.022(0.019) + u_{14j}$$
$$\beta_{15j} = 0.435(0.118) + u_{15j}$$

$$\begin{bmatrix} u_{0j} \\ u_{14j} \\ u_{15j} \end{bmatrix} \sim \mathrm{N}(0,\ \Omega_u) \ : \ \Omega_u = \begin{bmatrix} 0.006(0.003) & & \\ 0.002(0.003) & 0.005(0.002) & \\ -0.016(0.012) & 0.007(0.007) & 0.112(0.046) \end{bmatrix}$$

$$e_{ij} \sim \mathrm{N}(0,\ \sigma_e^2) \quad \sigma_e^2 = 0.314(0.020)$$

$-2{*}loglikelihood = 2914.935$(1657 of 2532 cases in use)

Coefficients, standard errors and significance for rural households

	Expected Relationship	Coefficient	(Std Error)	t	
H1_EDUL_Z	+	-0.021	(0.018)	-1.167	
H2_LITS_Z	+	0.087	(0.017)	5.118	***
H3_FTRN_Z	+	0.085	(0.024)	3.542	***
H4_HLTH_Z	-	0.009	(0.020)	0.45	
S1_TIME_Z	+	-0.039	(0.017)	-2.294	
N1_LOWN_Z	+	0.045	(0.018)	2.5	*
N1_LRNT_Z	+	-0.002	(0.009)	-0.222	
N2_LCOW_Z	+	-0.010	(0.015)	-0.667	
N3_LMED_Z	+	0.007	(0.012)	0.583	
N4_LSML_Z	+	-0.026	(0.013)	-2	*
N5_LDFT_Z	+	-0.028	(0.010)	-2.8	**
N6_AGWK_Z		-0.044	(0.010)	-4.4	***
P1_NBED_Z	+	0.205	(0.017)	12.059	***
P2_ELEC_Z	+	0.022	(0.019)	1.158	
P3_CPBS_Z		0.435	(0.118)	3.686	***
P4_CPAG_Z	+	0.015	(0.029)	0.517	
F1_LPDM_Z	+	0.089	(0.014)	6.357	***
F2_LPSC_Z	+	0.003	(0.004)	0.75	
F3_TRDM_Z		-0.073	(0.019)	-3.842	***
F4_TRSC_Z	+	0.133	(0.040)	3.325	***
F5_RTDM_Z	+	-0.008	(0.020)	-0.4	
F6_RTSC_Z	+	0.052	(0.045)	1.156	
F7_PNDM_Z	+	0.008	(0.037)	0.216	
F8_PNSC_Z	+	0.004	(0.056)	0.071	
F9_CRDM_Z		0.044	(0.012)	3.667	***
F10_CRSC_Z	+	-0.043	(0.031)	-1.387	
NC1_DRY_Z	-	-0.031	(0.028)	-1.107	
NC2_LAND_Z	+	0.007	(0.021)	0.333	
NC3_SLP_Z	-	-0.071	(0.032)	-2.219	*
NC4_NVEG_Z	+	-0.010	(0.030)	-0.333	
PC1_ACC_Z	-	-0.007	(0.021)	-0.333	

P1_NBED_Z *NC3_SLP_Z	0.043	(0.013)	3.308	***
F4_TRSC_Z *NC3_SLP_Z	0.072	(0.043)	1.674	
F10_CRSC_Z*NC3_SLP_Z	0.102	(0.043)	2.372	*

* Significant at the 95% level; ** significant at the 99% level; *** significant at the 99.9% level

Appendix 4: Changes in the household composition of districts over time

The comparison of well-being responses through consumption and poverty indicators assumes that the same households are included in the district level aggregates for both time periods. Two reasons can be envisaged for the violation of this assumption. Firstly households are liable to appear in different districts due to migration within Ecuador (Katz, 1998), or the structure of households and districts could change dramatically through emigration (Izquierdo, 2004). Secondly, boundary changes, or the creation of new administrative units, could cause the same household in the same location to be included in different districts in different time periods.

Migration in Ecuador during the 1990’s

The likely effects on changes in consumption or poverty due to migration would probably be positive for households sending members and receiving remittances, and potentially negative for districts receiving migrants.

Studies on migration of Ecuador’s population show that there was considerable emigration between 1997 and 2001 (Jokisch, 2002) and that richer households were more likely to send members overseas than poorer households (Izquierdo, 2004). During the 1990’s and particularly after the El Niño event the patterns of emigration changed dramatically and almost every province contributed to the emigrants (Jokisch and Pribilsky, 2004). Migration within Ecuador was traditionally from the Andean region to agricultural plantations in the coastal region, and was also responsible for much of the population increase in the Amazon region. In this latter case migrants responded to the development of oil producing areas in the northern Amazon region and subsequently for spontaneous colonisation of forest for agricultural land and livestock activities. During the 1990’s however the greatest changes in population distribution in the Amazon region have been due to rural-urban and rural-rural migration (Barbieri, 2005). As in previous decades in-migration was responsible for much of the population growth in urban locations during the 1990’s but rural population also grew in that decade (Cerrutti and Bertoncello, 2003).

Urban areas have likely received migrants from rural areas during the 1990's thus it is difficult to assess the contribution of this in-migration on changes in consumption or poverty levels. The rates of rural-urban migration do not seem to have increased as dramatically as migration abroad, a factor which is probably due to the crisis which followed the El Niño event which was not limited to specific geographic areas within Ecuador.

Changes in district boundaries

Boundary changes, in contrast, can have a systematic effect on the districts involved, depending on how the change has occurred. The number of districts in Ecuador increased between 1990 and 2001; new counties were created from districts, while other large or populous districts were split. The former case would not affect the comparison of household well-being so long as old and new districts could be identified, but where districts are split the composition of richer and poorer households could change.

The number of districts for which data are available in the 1990 census is 911[82]. The full extent of these districts is not fully known as there is no digital dataset for 1990. The earliest digital spatial dataset is for 1995, by which time a further 37 new districts had been created. During the same period a new province (Orellana) was created and the number of counties in continental Ecuador increased from 167 to 211 – an increase of 44[83]. In the period 1995 to 2001, the number of districts increased by a further 35 and in the same period 2 counties were added (Table 60). Two districts (Guanujo, in Bolívar province and El Cambio in El Oro), appear on the spatial dataset for 1995 but not on some later datasets. Neither are data available for these districts for poverty or consumption from 2001.

[82] Excluding districts in the Galapagos Islands (which are not considered in this study), and 'non-delimited' areas.

[83] It appears that Orellana was created in 1998, the data source therefore seems to be a mix of dates, perhaps using the borders from 1995 but changing the names of provinces and codes for Orellana province.

Table 60 Changes in number of districts and counties in Ecuador 1990-2001

Province	counties 1990[a]	districts 1990[a]	counties 1995[b]	districts 1995[b]	counties 2001[c]	districts 2001[c]
Azuay	9	67	14	73	14	74
Bolivar	6	27	7	27	7	26
Cañar	4	31	7	32	7	33
Carchi	5	29	6	31	6	32
Cotopaxi	6	40	7	35	7	40
Chimborazo	9	53	10	53	10	54
El Oro	14	56	14	58	14	62
Esmeraldas	5	58	7	63	7	63
Guayas	21	60	28	62	28	63
Imbabura	6	42	6	42	6	42
Loja	15	85	16	88	16	90
Los Rios	9	25	12	25	12	27
Manabi	16	66	21	68	22	75
Morona Santiago	6	47	10	54	11	57
Napo	8	37	5	22	5	23
Pastaza	2	19	4	20	4	20
Pichincha	6	66	9	63	9	66
Tungurahua	9	51	9	50	9	53
Zamora Chinchipe	5	25	8	30	8	30
Sucumbios	6	27	7	32	7	33
Orellana	0	0	4	20	4	20
Total	**167**	**911**	**211**	**948**	**213**	**983**

Sources: [a] Larrea et al., 1996; [b] Larrea et al., 1999; [c] Larrea, 2005

The spatial datasets of districts are from 1995 and 1998 so for some of the districts created after 1998 there will be no spatial reference and these will not be included in the analysis of vulnerable areas. However the consumption aggregates and poverty indicators for some of the ‘new’ districts have been constructed using census ward information (Larrea, personal communication) allowing comparison between 1990 and 2001 (Figure 66).

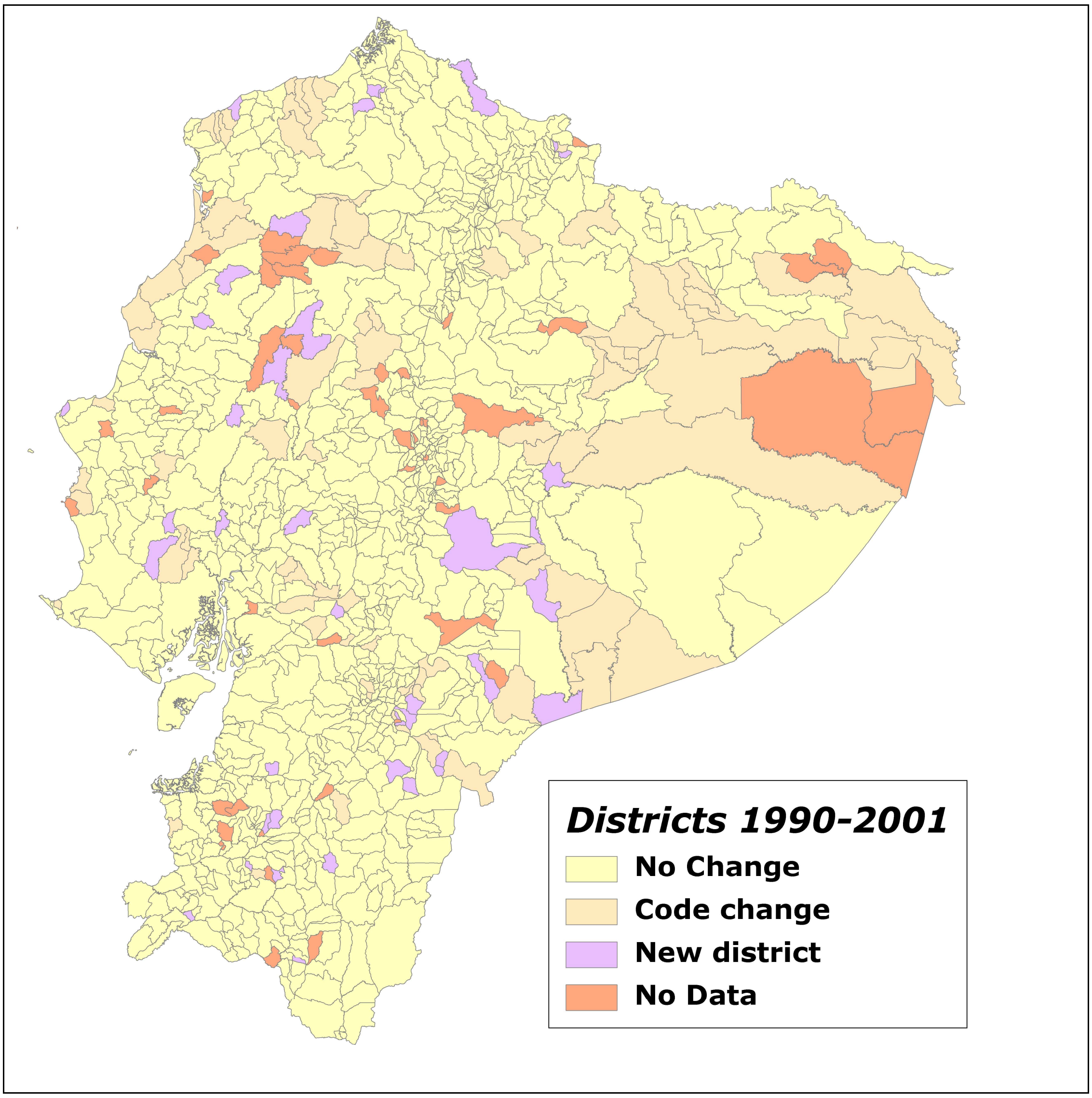

Figure 66. Changes in districts 1990-2001

Appendix 5: Associations between changes in well-being and impacts of 1997-98 El Niño event

Consumption and proportion of the population affected

Contingency table of the dummy variable for better/worse consumption z scores 1990-2001 * dummy variable for population affected

Change in consumption z scores 1990-2001		Population affected, dead or injured: No	Population affected, dead or injured: Yes	Total
Worse	Count	276	182	458
	Expected	271.6	186.4	
Better	Count	285	203	488
	Expected	289.4	198.6	
Total	Count	561	385	946

Contingency table of the classified better/worse consumption z scores 1990-2001 * dummy variable for population affected

Change in consumption z-scores 1990-2001			Population affected, dead or injured: No	Population affected, dead or injured: Yes	Total
Worse	< -1	Count	32	21	53
		Expected	31.4	21.6	
	-1 to 0	Count	244	161	405
		Expected	240.2	164.8	
Better	0 to 1	Count	251	190	441
		Expected	261.5	179.5	
	> 1	Count	34	13	47
		Expected	27.9	19.1	
	Total	Count	561	385	946

Poverty and population affected by El Niño

Contingency table of the dummy variable for better/worse poverty headcount ratio z-scores 1990-2001 * dummy variable for population affected

Change in poverty headcount ratio 1990-2001	Population affected, dead or injured: No	Population affected, dead or injured: Yes	Total

Worse	Count	241	230	471
	Expected	279.1	191.9	
Better	Count	316	153	469
	Expected	277.9	191.1	
Total	Count	557	383	940

Contingency table of the classified better/worse poverty headcount z scores 1990-2001 * dummy variable for population affected

Change in poverty headcount ratio z-scores 1990-2001			Population affected, dead or injured		Total
			No	Yes	
Worse	> 1	Count	48	31	79
		Expected	46.8	32.2	
	0 to 1	Count	193	199	392
		Expected	232.3	159.7	
Better	-1 to 0	Count	260	136	396
		Expected	234.7	161.3	
	< -1	Count	56	17	73
		Expected	43.3	29.7	
	Total	Count	557	383	940

Consumption and rainfall anomalies

Contingency table of the dummy variable for better/worse consumption z scores 1990-2001 * size of rainfall anomalies during the 1997-98 El Niño event

Change in consumption z scores 1990-2001		1997-98 Rainfall anomaly		Total
		Less than 100%	Greater than 100%	
Worse	Count	277	181	458
	Expected	274.0	184.0	
Better	Count	289	199	488
	Expected	292.0	196.0	
Total	Count	699	247	946

Contingency table of the classified better/worse consumption z-scores 1990-2001 * size of rainfall anomalies during the 1997-98 El Niño event

Change in consumption z-scores 1990-2001	1997-98 Rainfall anomaly		Total
	Less than 100%	Greater than	

				100%	
Worse	< -1	Count	23	30	53
		Expected	31.7	21.3	
	-1 to 0	Count	254	150	404
		Expected	241.7	162.3	
Better	0 to 1	Count	249	193	442
		Expected	264.5	177.5	
	> 1	Count	40	7	47
		Expected	28.1	18.9	
	Total	Count	566	380	946

Poverty and precipitation anomalies

Contingency table of the dummy variable for better/worse poverty headcount ratio z-scores 1990-2001 * size of rainfall anomalies during the 1997-98 El Niño event

Change in poverty headcount ratio z-scores 1990-2001		1997-98 Rainfall anomaly		Total
		Less than 100%	Greater than 100%	
Worse	Count	228	243	471
	Expected	280.6	190.4	
Better	Count	332	137	469
	Expected	279.4	189.6	
Total	Count	560	380	940

Contingency table of the classified better/worse poverty headcount z-scores 1990-2001 * size of rainfall anomalies during the 1997-98 El Niño event

Change in poverty headcount ratio z-scores 1990-2001			1997-98 Rainfall anomaly		Total
			Less than 100%	Greater than 100%	
Worse	> 1	Count	42	37	79
		Expected	47.1	31.9	
	0 to 1	Count	186	206	392
		Expected	233.5	158.5	
Better	-1 to 0	Count	271	125	396
		Expected	235.9	160.1	
	< -1	Count	61	12	73
		Expected	43.5	29.5	
	Total	Count	560	380	940

Consumption and vulnerability to agricultural losses

Contingency table of the dummy variable for better/worse consumption z scores 1990-2001 * districts vulnerable to losses in agricultural income due to the 1997-98 El Niño event

Change in consumption z scores 1990-2001		Losses in agricultural income: Not vulnerable	Losses in agricultural income: Vulnerable	Total
Worse	Count	380	78	458
	Expected	383.9	74.1	
Better	Count	413	75	488
	Expected	409.1	78.9	
Total	Count	793	153	946

Contingency table of the classified better/worse consumption z scores 1990-2001 * districts vulnerable to losses in agricultural income due to the 1997-98 El Niño event

Change in consumption z-scores 1990-2001			Losses in agricultural income: Not vulnerable	Losses in agricultural income: Vulnerable	Total
Worse	< -1	Count	43	10	53
		Expected	44.4	8.6	
	-1 to 0	Count	337	67	404
		Expected	339.5	65.5	
Better	0 to 1	Count	368	74	442
		Expected	369.7	71.3	
	> 1	Count	45	2	47
		Expected	39.4	7.6	
	Total	Count	793	153	946

Poverty and vulnerability to agricultural losses

Contingency table of the dummy variable for better/worse poverty headcount ratio z-scores 1990-2001 * districts vulnerable to losses in agricultural income due to the 1997-98 El Niño event

Change in poverty headcount ratio z-scores 1990-2001		Losses in agricultural income: Not vulnerable	Losses in agricultural income: Vulnerable	Total
Worse	Count	339	132	471
	Expected	394.3	76.7	

Better	Count	448	21	469
	Expected	392.7	76.3	
Total	Count	787	153	940

Contingency table of the classified better/worse poverty headcount ratio z-scores 1990-2001 * districts vulnerable to losses in agricultural income due to the 1997-98 El Niño event

Change in poverty headcount ratio z-scores 1990-2001			Losses in agricultural income		Total
			Not vulnerable	Vulnerable	
Worse	> 1	Count	66	13	79
		Expected	66.1	12.9	
	0 to 1	Count	273	119	392
		Expected	328.2	63.8	
Better	-1 to 0	Count	379	17	396
		Expected	331.5	64.5	
	< -1	Count	69	4	73
		Expected	61.1	11.9	
	Total	Count	787	153	940

Consumption and vulnerability to health risks

Contingency table of the dummy variable for better/worse consumption z scores 1990-2001 * districts vulnerable to health risks due to the 1997-98 El Niño event

Change in consumption z scores 1990-2001		Vulnerable to health risks		Total
		Not vulnerable	Vulnerable	
Worse	Count	320	138	458
	Expected	339.9	118.1	
Better	Count	382	106	488
	Expected	362.1	125.9	
Total	Count	702	244	946

Contingency table of the classified better/worse consumption z scores 1990-2001 * districts vulnerable to health risks due to the 1997-98 El Niño event

Change in consumption z-scores 1990-2001			Vulnerable to health risks		Total
			Not vulnerable	Vulnerable	
Worse	< -1	Count	25	28	53
		Expected	39.3	13.7	
	-1 to 0	Count	295	109	404

		Expected	299.8	104.2	
Better	0 to 1	Count	336	106	442
		Expected	328.0	114.0	
	> 1	Count	46	1	47
		Expected	34.9	12.1	
	Total	Count	702	244	946

Poverty and vulnerability to health risks

Contingency table of the dummy variable for better/worse poverty headcount ratio z-scores 1990-2001 * districts vulnerable to health risks due to the 1997-98 El Niño event

Change in poverty headcount ratio z-scores 1990-2001		Vulnerable to health risks		Total
		Not vulnerable	Vulnerable	
Worse	Count	261	210	471
	Expected	348.7	122.3	
Better	Count	435	34	469
	Expected	347.3	121.7	
Total	Count	696	244	940

Contingency table of the classified better/worse poverty headcount ratio z-scores 1990-2001 * districts vulnerable to health risks due to the 1997-98 El Niño event

Change in poverty headcount ratio z-scores 1990-2001			Vulnerable to health risks		Total
			Not vulnerable	Vulnerable	
Worse	> 1	Count	36	43	79
		Expected	58.5	20.5	
	0 to 1	Count	225	167	392
		Expected	290.2	101.8	
Better	-1 to 0	Count	363	33	396
		Expected	293.2	102.8	
	< -1	Count	72	1	73
		Expected	54.1	18.9	
	Total	Count	696	244	940

Appendix 6: Soil Metadata

http://www.uazuay.edu.ec/promsa/contenido_cd/metadatos.htm

The information was taken from the project "Generation of Georeferenced Information for the Development of the Agricultural Sector", undertaken in the cooperation convention framework between the ministry of agriculture and livestock (Ministerio de Agricultura y Ganadería – MAG), the Centre for Integrated Remote Sensing Survey of Natural Resources (Centro de Levantamientos Integrados de Recursos Naturales por Sensores Remotos - CLIRSEN), and the Inter-American Institute of Cooperation for Agriculture (Instituto Interamericano de Cooperación para la Agricultura - IICA).

The base information, the soil units and slope units are taken from soil maps from the national programme for agrarian regionalisation (Programa Nacional de Regionalización Agrária – PRONAREG) at scales of 1:500,000 for the Amazon region, 1:200,000 for the coastal region and a scale of 1:50,000 in the Andean region. These individual maps have little metadata regarding the field methodology other than fieldwork was carried out at various dates throughout the 1970's and 1980's with technical assistance from ORSTOM. DINAREN are now the agency responsible for this database.

The database contains information on:

Map sheet	Soil class	Soil order	Soil pH
Freatic layer	Drainage	Erodibility	Fertility
Liability to flood	Organic material	Rockiness	Slope
Depth	Texture	Toxicity	Salinity

Description of variables:

The SLOPE variable considers the relief and the impact on tillage and on the movement of water across the land. The slope categories were categorised in the following manner:

CLASS	RANGE (%)
1	0-5
2	5-12
3	12-25
4	25-50
5	50-70
6	>70

The TEXTURE variable defines each class for the content or proportion of the particular components of the soil. The categories are grouped in the following manner:

1	g	Coarse sandy	Fine, medium, coarse (11), sandy loam (12)
2	mg	Moderately coarse	Fine to coarse sandy loam (21), silty loam (22)
3	m	Medium	loam (31), silty (32), clay loam (< 35% of clay) (33), sandy clay loam (34), sandy silty loam (35)
4	f	Fine	Clay loam (>35%) (41), clay (42), sandy clay (43), clay loam (44)
5	mf	very fine	Clay (> 60%) (51)

The DEPTH variable considers the depth of the layers of soil up to a point in which the roots can reach without difficulty. The categories were considered in the following way:

1	s	Superficial	0 – 20 cm
2	pp	Shallow	20 – 50 cm
3	m	Moderately deep	50 – 100 cm
4	p	deep	> 100 cm

The ROCKINESS variable captures the content of stones and rocks that can interfere with tillage and plant growth. The categories are the following.

1	s	Without	(<10%)
2	p	Few	(10 – 25%)
3	fr	Frequent	(25 – 50%)
4	a	Abundant	(50 – 75%)
5	r	Stoney or rocky	(> 75%)

In the field DRAINAGE is defined the capacity for drainage and infiltration of water in the soil. The categories are the following

1	e	Excessive
2	b	Good
3	m	Moderate
4	md	Poorly drained (imperfect)

The variable FLOODING describes if soils are permanently saturated due to permanent water or flooding caused by stagnant water of breached rivers.

1	a	none
2	b	with water < than 3 months
3	c	with water 3 - 6 months
4	d	flooded all of the year

The field FREATIC LAYER is the level of the water table. Categories were grouped in the following ranges.

1	s	Superficial	0 – 20 cm
2	pp	Shallow	20 –50 cm
3	m	Moderately deep	50 – 100 cm
4	p	Deep	>100 cm

The pH variable describes the acidity measured by the concentration of hydrogen ions.

1	mac	very acid	< 4.5
2	a	acid	4.5 – 5.5
3	lac	slightly acid	5.6 – 6.5
4	n	neutral	6.6 – 7.4
5	mal	moderately alkaline	7.5 – 8.5
6	al	alkaline	> 8.5

The ORGANIC MATERIAL field is the grade of decomposition of the remains of vegetables and animals. The ranges are.

1	mb	Very low	< 1 %
2	b	Low	1 – 2 %
3	m	Medium	2 – 4 %
4	a	High	4 –10 %
5	ma	Very high	> 10 %

SALINITY is the concentration of salts in the soil, categories ere established with the following ranges.

1	s	without	0 – 2 mmhos/cm
2	L	light	2 – 4 mmhos/cm
3	m	medium	4 – 8 mmhos/cm
4	a	high	8–16 mmhos/cm
5	ma	very high	> 16 mmhos/cm

TOXICITY is the content of elements considered damaging to the growth of plants.

1	s	without
2	l	light
3	m	medium
4	a	high

The level of FERTILITY is the content in the soil of the nutrients necessary for plant growth. This is calculated based on the pH, organic matter, base saturation, and cation exchange capacity.

1	mb	very low
2	b	low
3	m	medium
4	a	high

The variable ERODIBILTY variable is the danger or risk of erosion.

1	n	none
2	l	light
3	m	moderate
4	a	high
5	s	severe (eroded)

Appendix 7: Flood Model Arc Macro Language script

Methodology used to derive flood areas based on Rodda (2005), produced flood.aml

Three scenarios:
(a) Flood level is constant, no buffers (uses aml flood_no_buf)
(b) Flood level is constant, but buffers are dependent on discharge (uses aml flood_buf)
(c) Flood level and buffers are dependent on discharge (uses aml flood_buf_lev)

Flood levels of 2m, 5m and 10m based on maximum floods expected according to historical data

Step 1: merge raw hydrosheds data
CON_HY_DEM = mosaic (n00w085_con , n00w080_con , s05w085_con , s05w080_con)

Step 2: Create flow accumulation and flow direction grids
Flowdir = FLOWDIRECTION (CON_HY_DEM , NORMAL)
Faccgrid = FLOWACCUMULATION(Flowdir)

Step 3: Stream order grids created using contributing area (number of cells), values based on biggest contributing area found in study region (13124790 cells)

```
STRGRID10 = int ( con ( faccgrid >= 1312480 , 1 ) )
STRGRID05 = int ( con ( faccgrid >=  328120 , 1 ) )
STRGRID04 = int ( con ( faccgrid >=  209997 , 1 ) )
STRGRID03 = int ( con ( faccgrid >=  118123 , 1 ) )
STRGRID02 = int ( con ( faccgrid >=   52499 , 1 ) )
STRGRID01 = int ( con ( faccgrid >=   13124 , 1 ) )
STRGRID00 = int ( con ( faccgrid >=    1000 , 1 ) )
```

Step 4: Stream allocation grids constructed from stream order grids using watershed function to define the contributing area of all cells in the stream order grids
Watershed function in ArcGIS is used to define the contributing area for each point on the stream network; the catchment is given the value of the elevation of the stream to which it contributes, i.e. the pour point or lowest elevation of the catchment.

```
STRM_ALLOC10  = watershed ( flowdir , ( strgrid10  * con ( con_hy_dem >= 0 , con_hy_dem , 0 )))
STRM_ALLOC05  = watershed ( flowdir , ( strgrid05  * con ( con_hy_dem >= 0 , con_hy_dem , 0 )))
STRM_ALLOC04  = watershed ( flowdir , ( strgrid04  * con ( con_hy_dem >= 0 , con_hy_dem , 0 )))
STRM_ALLOC03  = watershed ( flowdir , ( strgrid03  * con ( con_hy_dem >= 0 , con_hy_dem , 0 )))
STRM_ALLOC02  = watershed ( flowdir , ( strgrid02  * con ( con_hy_dem >= 0 , con_hy_dem , 0 )))
```

STRM_ALLOC01 = watershed (flowdir , (strgrid01 * con (con_hy_dem >= 0 , con_hy_dem , 0)))
STRM_ALLOC00 = watershed (flowdir , (strgrid00 * con (con_hy_dem >= 0 , con_hy_dem , 0)))

Step 5: Create buffers around streams using a Euclidian distance in 100 metres (degrees*0.000833) so strbuf10 gives a 10km buffer

STRBUF10 = floor (eucdistance (strgrid10 , # , # , (100 * 0.0008333)))
STRBUF05 = floor (eucdistance (strgrid05 , # , # , (50 * 0.0008333)))
STRBUF04 = floor (eucdistance (strgrid04 , # , # , (40 * 0.0008333)))
STRBUF03 = floor (eucdistance (strgrid03 , # , # , (30 * 0.0008333)))
STRBUF02 = floor (eucdistance (strgrid02 , # , # , (20 * 0.0008333)))
STRBUF01 = floor (eucdistance (strgrid01 , # , # , (10 * 0.0008333)))
STRBUF00 = floor (eucdistance (strgrid00 , # , # , (5 * 0.0008333)))

Step 6: Create flood grids using con statement based on incrementing water level according to the pour point of the stream allocation grid constricted by buffer grid

FLOOD10 = con ((con_hy_dem - (strm_alloc10 + 10 + strbuf10)) < 0 , 1)
FLOOD05 = con ((con_hy_dem - (strm_alloc05 + 5 + strbuf05)) < 0 , 1)
FLOOD04 = con ((con_hy_dem - (strm_alloc04 + 4 + strbuf04)) < 0 , 1)
FLOOD03 = con ((con_hy_dem - (strm_alloc03 + 3 + strbuf03)) < 0 , 1)
FLOOD02 = con ((con_hy_dem - (strm_alloc02 + 2 + strbuf02)) < 0 , 1)
FLOOD01 = con ((con_hy_dem - (strm_alloc01 + 1 + strbuf01)) < 0 , 1)
FLOOD00 = con ((con_hy_dem - (strm_alloc00 + 0.5 + strbuf00)) < 0 , 1)

Step 7: Create floodtot grid from individual flood grids

FLOODTOT = merge (flood00 , flood01 , flood02 , flood03 , flood04 , flood05 , flood10)

Step 8: Subtract the stream grid from the flood area to get the total area flooded and reclass so that values are either 1 (flooded) or 0 (non-flooded or stream)

FLOOD_nstrm = reclass (FLOODTOT – strgrid00)

Step 9: Convert floodtot to shape

FLOODTOT.SHP = gridshape (FLOOD_nstrm , NOWEED)

' A.Farrow 03/09/2008 CIAT and UEA

' this macro creates points from the flood model runs
' then runs stats on these using the cellsize of the popualtion grids
' this avoids resampling errors when resample is run in grid on the original grids
' which would take the centre grid cell and use that value rather than a mean value for all the cells

```
w \hydrosheds

grid

'set the grid environment variables for cellsize and extent

setcell X_FL_clip
setwindow X_FL_clip

' -/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/

' STEP 1 & 2: convert raster to vector points and run pointstats on the point shapefiles and then delete pointfiles to make room for next one

X_point = gridpoint ( X_FL_clip , GRID_CODE )

'set the grid environment variables for cellsize and extent

setcell lspop2006_utm
setwindow lspop2006_utm

X_POP = PointStats( X_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill X_point

setcell Y_FL_clip
setwindow Y_FL_clip

' -/-/-/-/-/-/


Y_point = gridpoint ( Y_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Y_POP = PointStats( Y_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Y_point
```

```
setcell Z_FL_clip
setwindow Z_FL_clip

' -/-/-/-/-/-/

Z_point = gridpoint ( Z_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Z_POP = PointStats( Z_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Z_point

setcell X1_FL_clip
setwindow X1_FL_clip

' -/-/-/-/-/-/

X1_point = gridpoint ( X1_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

X1_POP = PointStats( X1_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill X1_point

setcell X2_FL_clip
setwindow X2_FL_clip

' -/-/-/-/-/-/

X2_point = gridpoint ( X2_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

X2_POP = PointStats( X2_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )
```

```
kill X2_point

setcell X3_FL_clip
setwindow X3_FL_clip

' -/-/-/-/-/-/

X3_point = gridpoint ( X3_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

X3_POP = PointStats( X3_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill X3_point

setcell Y1_FL_clip
setwindow Y1_FL_clip

' -/-/-/-/-/-/

Y1_point = gridpoint ( Y1_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Y1_POP = PointStats( Y1_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Y1_point

setcell Y2_FL_clip
setwindow Y2_FL_clip

' -/-/-/-/-/-/

Y2_point = gridpoint ( Y2_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm
```

```
Y2_POP = PointStats( Y2_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Y2_point

setcell Y3_FL_clip
setwindow Y3_FL_clip

' -/-/-/-/-/-/

Y3_point = gridpoint ( Y3_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Y3_POP = PointStats( Y3_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Y3_point

setcell z1_FL_clip
setwindow z1_FL_clip

' -/-/-/-/-/-/

z1_point = gridpoint ( z1_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

z1_POP = PointStats( z1_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill z1_point

setcell z2_FL_clip
setwindow z2_FL_clip

' -/-/-/-/-/-/

z2_point = gridpoint ( z2_FL_clip , GRID_CODE )
```

```
setcell lspop2006_utm
setwindow lspop2006_utm

z2_POP = PointStats( z2_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill z2_point

setcell z3_FL_clip
setwindow z3_FL_clip

' -/-/-/-/-/-/

z3_point = gridpoint ( z3_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

z3_POP = PointStats( z3_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill z3_point

setcell X1L_FL_clip
setwindow X1L_FL_clip

' -/-/-/-/-/-/

X1L_point = gridpoint ( X1L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

X1L_POP = PointStats( X1L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill X1L_point

setcell X2L_FL_clip
setwindow X2L_FL_clip

' -/-/-/-/-/-/
```

```
X2L_point = gridpoint ( X2L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

X2L_POP = PointStats( X2L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill X2L_point

setcell X3L_FL_clip
setwindow X3L_FL_clip

' -/-/-/-/-/-/

X3L_point = gridpoint ( X3L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

X3L_POP = PointStats( X3L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill X3L_point

setcell Y1L_FL_clip
setwindow Y1L_FL_clip

' -/-/-/-/-/-/

Y1L_point = gridpoint ( Y1L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Y1L_POP = PointStats( Y1L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Y1L_point

setcell Y2L_FL_clip
setwindow Y2L_FL_clip
```

```
' -/-/-/-/-/-/

Y2L_point = gridpoint ( Y2L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Y2L_POP = PointStats( Y2L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Y2L_point

setcell Y3L_FL_clip
setwindow Y3L_FL_clip

' -/-/-/-/-/-/

Y3L_point = gridpoint ( Y3L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Y3L_POP = PointStats( Y3L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Y3L_point

setcell Z1L_FL_clip
setwindow Z1L_FL_clip

' -/-/-/-/-/-/

Z1L_point = gridpoint ( Z1L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Z1L_POP = PointStats( Z1L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Z1L_point

setcell Z2L_FL_clip
```

```
setwindow Z2L_FL_clip

' -/-/-/-/-/-/

Z2L_point = gridpoint ( Z2L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Z2L_POP = PointStats( Z2L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Z2L_point

setcell Z3L_FL_clip
setwindow Z3L_FL_clip

' -/-/-/-/-/-/

Z3L_point = gridpoint ( Z3L_FL_clip , GRID_CODE )

setcell lspop2006_utm
setwindow lspop2006_utm

Z3L_POP = PointStats( Z3L_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )

kill Z3L_point

' -/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/

' STEP 3: get population for the flooded areas


X_LSCAN_POP = Int ( ( X_POP ) * lspop2006_utm )
X_GRUMP_POP = Int ( ( X_POP ) * sauds95g_lscn )

Y_LSCAN_POP = Int ( ( Y_POP ) * lspop2006_utm )
Y_GRUMP_POP = Int ( ( Y_POP ) * sauds95g_lscn )

Z_LSCAN_POP = Int ( ( Z_POP ) * lspop2006_utm )
Z_GRUMP_POP = Int ( ( Z_POP ) * sauds95g_lscn )
```

```
' -/-/-/-/-/-/

X1_LSCAN_POP = Int ( ( X1_POP ) * lspop2006_utm )
X1_GRUMP_POP = Int ( ( X1_POP ) * sauds95g_lscn )

Y1_LSCAN_POP = Int ( ( Y1_POP ) * lspop2006_utm )
Y1_GRUMP_POP = Int ( ( Y1_POP ) * sauds95g_lscn )

Z1_LSCAN_POP = Int ( ( Z1_POP ) * lspop2006_utm )
Z1_GRUMP_POP = Int ( ( Z1_POP ) * sauds95g_lscn )

X2_LSCAN_POP = Int ( ( X2_POP ) * lspop2006_utm )
X2_GRUMP_POP = Int ( ( X2_POP ) * sauds95g_lscn )

Y2_LSCAN_POP = Int ( ( Y2_POP ) * lspop2006_utm )
Y2_GRUMP_POP = Int ( ( Y2_POP ) * sauds95g_lscn )

Z2_LSCAN_POP = Int ( ( Z2_POP ) * lspop2006_utm )
Z2_GRUMP_POP = Int ( ( Z2_POP ) * sauds95g_lscn )

X3_LSCAN_POP = Int ( ( X3_POP ) * lspop2006_utm )
X3_GRUMP_POP = Int ( ( X3_POP ) * sauds95g_lscn )

Y3_LSCAN_POP = Int ( ( Y3_POP ) * lspop2006_utm )
Y3_GRUMP_POP = Int ( ( Y3_POP ) * sauds95g_lscn )

Z3_LSCAN_POP = Int ( ( Z3_POP ) * lspop2006_utm )
Z3_GRUMP_POP = Int ( ( Z3_POP ) * sauds95g_lscn )

' -/-/-/-/-/-/

X1L_LSCAN_POP = Int ( ( X1L_POP ) * lspop2006_utm )
X1L_GRUMP_POP = Int ( ( X1L_POP ) * sauds95g_lscn )

Y1L_LSCAN_POP = Int ( ( Y1L_POP ) * lspop2006_utm )
Y1L_GRUMP_POP = Int ( ( Y1L_POP ) * sauds95g_lscn )

Z1L_LSCAN_POP = Int ( ( Z1L_POP ) * lspop2006_utm )
Z1L_GRUMP_POP = Int ( ( Z1L_POP ) * sauds95g_lscn )
```

```
X2L_LSCAN_POP = Int ( ( X2L_POP ) * lspop2006_utm )
X2L_GRUMP_POP = Int ( ( X2L_POP ) * sauds95g_lscn )

Y2L_LSCAN_POP = Int ( ( Y2L_POP ) * lspop2006_utm )
Y2L_GRUMP_POP = Int ( ( Y2L_POP ) * sauds95g_lscn )

Z2L_LSCAN_POP = Int ( ( Z2L_POP ) * lspop2006_utm )
Z2L_GRUMP_POP = Int ( ( Z2L_POP ) * sauds95g_lscn )

X3L_LSCAN_POP = Int ( ( X3L_POP ) * lspop2006_utm )
X3L_GRUMP_POP = Int ( ( X3L_POP ) * sauds95g_lscn )

Y3L_LSCAN_POP = Int ( ( Y3L_POP ) * lspop2006_utm )
Y3L_GRUMP_POP = Int ( ( Y3L_POP ) * sauds95g_lscn )

Z3L_LSCAN_POP = Int ( ( Z3L_POP ) * lspop2006_utm )
Z3L_GRUMP_POP = Int ( ( Z3L_POP ) * sauds95g_lscn )

' -/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/

' STEP 4: zonal statistics for population of floods per parroquia

'set the grid environment variables for cellsize and extent

setcell X_LSCAN_POP
setwindow X_LSCAN_POP

X_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , X_LSCAN_POP    , all )
X_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , X_LSCAN_POP    , all )
X_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , X_GRUMP_POP    , all )
X_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , X_GRUMP_POP    , all )

Y_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Y_LSCAN_POP    , all )
Y_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Y_LSCAN_POP    , all )
Y_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Y_GRUMP_POP    , all )
Y_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Y_GRUMP_POP    , all )

Z_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Z_LSCAN_POP    , all )
Z_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Z_LSCAN_POP    , all )
```

```
Z_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Z_GRUMP_POP    , all )
Z_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Z_GRUMP_POP    , all )

' -/-/-/-/-/-/

X1_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , X1_LSCAN_POP    , all )
X1_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , X1_LSCAN_POP    , all )
X1_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , X1_GRUMP_POP    , all )
X1_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , X1_GRUMP_POP    , all )

Y1_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Y1_LSCAN_POP    , all )
Y1_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Y1_LSCAN_POP    , all )
Y1_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Y1_GRUMP_POP    , all )
Y1_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Y1_GRUMP_POP    , all )

Z1_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Z1_LSCAN_POP    , all )
Z1_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Z1_LSCAN_POP    , all )
Z1_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Z1_GRUMP_POP    , all )
Z1_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Z1_GRUMP_POP    , all )

X2_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , X2_LSCAN_POP    , all )
X2_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , X2_LSCAN_POP    , all )
X2_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , X2_GRUMP_POP    , all )
X2_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , X2_GRUMP_POP    , all )

Y2_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Y2_LSCAN_POP    , all )
Y2_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Y2_LSCAN_POP    , all )
Y2_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Y2_GRUMP_POP    , all )
Y2_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Y2_GRUMP_POP    , all )

Z2_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Z2_LSCAN_POP    , all )
Z2_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Z2_LSCAN_POP    , all )
Z2_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Z2_GRUMP_POP    , all )
Z2_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Z2_GRUMP_POP    , all )

X3_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , X3_LSCAN_POP    , all )
X3_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , X3_LSCAN_POP    , all )
X3_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , X3_GRUMP_POP    , all )
X3_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , X3_GRUMP_POP    , all )
```

```
Y3_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Y3_LSCAN_POP    , all )
Y3_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Y3_LSCAN_POP    , all )
Y3_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Y3_GRUMP_POP    , all )
Y3_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Y3_GRUMP_POP    , all )

Z3_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Z3_LSCAN_POP    , all )
Z3_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Z3_LSCAN_POP    , all )
Z3_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Z3_GRUMP_POP    , all )
Z3_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Z3_GRUMP_POP    , all )

' -/-/-/-/-/-/

X1L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , X1L_LSCAN_POP    , all )
X1L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , X1L_LSCAN_POP    , all )
X1L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , X1L_GRUMP_POP    , all )
X1L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , X1L_GRUMP_POP    , all )

Y1L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Y1L_LSCAN_POP    , all )
Y1L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Y1L_LSCAN_POP    , all )
Y1L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Y1L_GRUMP_POP    , all )
Y1L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Y1L_GRUMP_POP    , all )

Z1L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Z1L_LSCAN_POP    , all )
Z1L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Z1L_LSCAN_POP    , all )
Z1L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Z1L_GRUMP_POP    , all )
Z1L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Z1L_GRUMP_POP    , all )

X2L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , X2L_LSCAN_POP    , all )
X2L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , X2L_LSCAN_POP    , all )
X2L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , X2L_GRUMP_POP    , all )
X2L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , X2L_GRUMP_POP    , all )

Y2L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Y2L_LSCAN_POP    , all )
Y2L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Y2L_LSCAN_POP    , all )
Y2L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Y2L_GRUMP_POP    , all )
Y2L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Y2L_GRUMP_POP    , all )

Z2L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Z2L_LSCAN_POP    , all )
Z2L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Z2L_LSCAN_POP    , all )
Z2L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Z2L_GRUMP_POP    , all )
```

```
Z2L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Z2L_GRUMP_POP    , all )

X3L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , X3L_LSCAN_POP    , all )
X3L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , X3L_LSCAN_POP    , all )
X3L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , X3L_GRUMP_POP    , all )
X3L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , X3L_GRUMP_POP    , all )

Y3L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Y3L_LSCAN_POP    , all )
Y3L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Y3L_LSCAN_POP    , all )
Y3L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Y3L_GRUMP_POP    , all )
Y3L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Y3L_GRUMP_POP    , all )

Z3L_FL_ecu_lscn_tab    = zonalstats ( ecu_2001_hy , Z3L_LSCAN_POP    , all )
Z3L_FL_parr_lscn_tab   = zonalstats ( parr2001_hy , Z3L_LSCAN_POP    , all )
Z3L_FL_ecu_grmp_tab    = zonalstats ( ecu_2001_hy , Z3L_GRUMP_POP    , all )
Z3L_FL_parr_grmp_tab   = zonalstats ( parr2001_hy , Z3L_GRUMP_POP    , all )

q

' -/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/-/

' STEP 5: convert iNFO tab into .dbf files in ARC environment using infodbase command

infodbase X_FL_ecu_lscn_tab    X_FL_ecu_lscn.dbf
infodbase X_FL_parr_lscn_tab   X_FL_parr_lscn.dbf
infodbase X_FL_ecu_grmp_tab    X_FL_ecu_grmp.dbf
infodbase X_FL_parr_grmp_tab   X_FL_parr_grmp.dbf

infodbase Y_FL_ecu_lscn_tab    Y_FL_ecu_lscn.dbf
infodbase Y_FL_parr_lscn_tab   Y_FL_parr_lscn.dbf
infodbase Y_FL_ecu_grmp_tab    Y_FL_ecu_grmp.dbf
infodbase Y_FL_parr_grmp_tab   Y_FL_parr_grmp.dbf

infodbase Z_FL_ecu_lscn_tab    Z_FL_ecu_lscn.dbf
infodbase Z_FL_parr_lscn_tab   Z_FL_parr_lscn.dbf
infodbase Z_FL_ecu_grmp_tab    Z_FL_ecu_grmp.dbf
infodbase Z_FL_parr_grmp_tab   Z_FL_parr_grmp.dbf

infodbase X1_FL_ecu_lscn_tab   X1_FL_ecu_lscn.dbf
infodbase X1_FL_parr_lscn_tab  X1_FL_parr_lscn.dbf
```

```
infodbase X1_FL_ecu_grmp_tab   X1_FL_ecu_grmp.dbf
infodbase X1_FL_parr_grmp_tab  X1_FL_parr_grmp.dbf

infodbase Y1_FL_ecu_lscn_tab   Y1_FL_ecu_lscn.dbf
infodbase Y1_FL_parr_lscn_tab  Y1_FL_parr_lscn.dbf
infodbase Y1_FL_ecu_grmp_tab   Y1_FL_ecu_grmp.dbf
infodbase Y1_FL_parr_grmp_tab  Y1_FL_parr_grmp.dbf

infodbase Z1_FL_ecu_lscn_tab   Z1_FL_ecu_lscn.dbf
infodbase Z1_FL_parr_lscn_tab  Z1_FL_parr_lscn.dbf
infodbase Z1_FL_ecu_grmp_tab   Z1_FL_ecu_grmp.dbf
infodbase Z1_FL_parr_grmp_tab  Z1_FL_parr_grmp.dbf

infodbase X2_FL_ecu_lscn_tab   X2_FL_ecu_lscn.dbf
infodbase X2_FL_parr_lscn_tab  X2_FL_parr_lscn.dbf
infodbase X2_FL_ecu_grmp_tab   X2_FL_ecu_grmp.dbf
infodbase X2_FL_parr_grmp_tab  X2_FL_parr_grmp.dbf

infodbase Y2_FL_ecu_lscn_tab   Y2_FL_ecu_lscn.dbf
infodbase Y2_FL_parr_lscn_tab  Y2_FL_parr_lscn.dbf
infodbase Y2_FL_ecu_grmp_tab   Y2_FL_ecu_grmp.dbf
infodbase Y2_FL_parr_grmp_tab  Y2_FL_parr_grmp.dbf

infodbase Z2_FL_ecu_lscn_tab   Z2_FL_ecu_lscn.dbf
infodbase Z2_FL_parr_lscn_tab  Z2_FL_parr_lscn.dbf
infodbase Z2_FL_ecu_grmp_tab   Z2_FL_ecu_grmp.dbf
infodbase Z2_FL_parr_grmp_tab  Z2_FL_parr_grmp.dbf

infodbase X3_FL_ecu_lscn_tab   X3_FL_ecu_lscn.dbf
infodbase X3_FL_parr_lscn_tab  X3_FL_parr_lscn.dbf
infodbase X3_FL_ecu_grmp_tab   X3_FL_ecu_grmp.dbf
infodbase X3_FL_parr_grmp_tab  X3_FL_parr_grmp.dbf

infodbase Y3_FL_ecu_lscn_tab   Y3_FL_ecu_lscn.dbf
infodbase Y3_FL_parr_lscn_tab  Y3_FL_parr_lscn.dbf
infodbase Y3_FL_ecu_grmp_tab   Y3_FL_ecu_grmp.dbf
infodbase Y3_FL_parr_grmp_tab  Y3_FL_parr_grmp.dbf

infodbase Z3_FL_ecu_lscn_tab   Z3_FL_ecu_lscn.dbf
infodbase Z3_FL_parr_lscn_tab  Z3_FL_parr_lscn.dbf
```

```
infodbase Z3_FL_ecu_grmp_tab   Z3_FL_ecu_grmp.dbf
infodbase Z3_FL_parr_grmp_tab  Z3_FL_parr_grmp.dbf

infodbase X1L_FL_ecu_lscn_tab  X1L_FL_ecu_lscn.dbf
infodbase X1L_FL_parr_lscn_tab X1L_FL_parr_lscn.dbf
infodbase X1L_FL_ecu_grmp_tab  X1L_FL_ecu_grmp.dbf
infodbase X1L_FL_parr_grmp_tab X1L_FL_parr_grmp.dbf

infodbase Y1L_FL_ecu_lscn_tab  Y1L_FL_ecu_lscn.dbf
infodbase Y1L_FL_parr_lscn_tab Y1L_FL_parr_lscn.dbf
infodbase Y1L_FL_ecu_grmp_tab  Y1L_FL_ecu_grmp.dbf
infodbase Y1L_FL_parr_grmp_tab Y1L_FL_parr_grmp.dbf

infodbase Z1L_FL_ecu_lscn_tab  Z1L_FL_ecu_lscn.dbf
infodbase Z1L_FL_parr_lscn_tab Z1L_FL_parr_lscn.dbf
infodbase Z1L_FL_ecu_grmp_tab  Z1L_FL_ecu_grmp.dbf
infodbase Z1L_FL_parr_grmp_tab Z1L_FL_parr_grmp.dbf

infodbase X2L_FL_ecu_lscn_tab  X2L_FL_ecu_lscn.dbf
infodbase X2L_FL_parr_lscn_tab X2L_FL_parr_lscn.dbf
infodbase X2L_FL_ecu_grmp_tab  X2L_FL_ecu_grmp.dbf
infodbase X2L_FL_parr_grmp_tab X2L_FL_parr_grmp.dbf

infodbase Y2L_FL_ecu_lscn_tab  Y2L_FL_ecu_lscn.dbf
infodbase Y2L_FL_parr_lscn_tab Y2L_FL_parr_lscn.dbf
infodbase Y2L_FL_ecu_grmp_tab  Y2L_FL_ecu_grmp.dbf
infodbase Y2L_FL_parr_grmp_tab Y2L_FL_parr_grmp.dbf

infodbase Z2L_FL_ecu_lscn_tab  Z2L_FL_ecu_lscn.dbf
infodbase Z2L_FL_parr_lscn_tab Z2L_FL_parr_lscn.dbf
infodbase Z2L_FL_ecu_grmp_tab  Z2L_FL_ecu_grmp.dbf
infodbase Z2L_FL_parr_grmp_tab Z2L_FL_parr_grmp.dbf

infodbase X3L_FL_ecu_lscn_tab  X3L_FL_ecu_lscn.dbf
infodbase X3L_FL_parr_lscn_tab X3L_FL_parr_lscn.dbf
infodbase X3L_FL_ecu_grmp_tab  X3L_FL_ecu_grmp.dbf
infodbase X3L_FL_parr_grmp_tab X3L_FL_parr_grmp.dbf

infodbase Y3L_FL_ecu_lscn_tab  Y3L_FL_ecu_lscn.dbf
infodbase Y3L_FL_parr_lscn_tab Y3L_FL_parr_lscn.dbf
```

infodbase Y3L_FL_ecu_grmp_tab Y3L_FL_ecu_grmp.dbf
infodbase Y3L_FL_parr_grmp_tab Y3L_FL_parr_grmp.dbf

infodbase Z3L_FL_ecu_lscn_tab Z3L_FL_ecu_lscn.dbf
infodbase Z3L_FL_parr_lscn_tab Z3L_FL_parr_lscn.dbf
infodbase Z3L_FL_ecu_grmp_tab Z3L_FL_ecu_grmp.dbf
infodbase Z3L_FL_parr_grmp_tab Z3L_FL_parr_grmp.dbf

Appendix 8: Resampling in ArcGIS

The resampling method in the ArcGIS software is not suitable for averaging many cells as is the case when I need to resample the results of the landslide (or flood) models and create values of population affected per district. Even using the more complex resampling algorithms (BILINEAR and CUBIC) does not produce an average of all the values.

An alternative is the convert all the models cells into points and then use an alternative method to get an average for these cells for each cell in the population grid.

This needs to be tested first, so I have chosen a small test area which contains all the values in one of the landslide model results (slope*soils*anomaly). I converted the model cells to points and applied the following expression in the raster calculator, where 929 is the cell size.

```
PointStats( lslide_sus3_test1 , GRID_CODE ,  #  ,  MEAN , RECTANGLE , 929 )
```

To ensure that the expression works I choose one large cell, and select the 100 points that fall within it. I create a new layer and export this as a dbf file (pointstats_test1.dbf) and analyse the mean value. This value corresponds to the value of the cell in the new grid, showing that this method, while not perfect in terms of extra processing and storage is a good method of resampling from smaller to larger grids while maintaining the average values.

```
Ls1_lscan = PointStats( lslide_sus1_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE ,
929 )
```

```
Ls3_lscan = PointStats( lslide_sus3_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE ,
929 )
```

These resampled grids are then used to calculate the sum of the population within each e.g.

```
Ls3_lscan_pop = Int(([Ls3_lscan]) * [lspop2002_utm]) / 100)

f21_lscan_pop  =   Int(([fld21_lscan]) * [lspop2002_utm])
FLD08_LSCAN = PointStats( flood_08_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE
, 929 )
F08_lscan_pop  =   Int(([fld08_lscan]) * [lspop2002_utm])

FLD01_LSCAN = PointStats( flood_01_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE
, 929 )
F01_lscan_pop  =   Int(([fld01_lscan]) * [lspop2002_utm])

FLD12_LSCAN = PointStats( flood_12_point , GRID_CODE ,  #  ,  MEAN , RECTANGLE
, 929 )
F12_lscan_pop  =   Int(([fld12_lscan]) * [lspop2002_utm])
```

This is repeated for the GRUMP population data (resampled to landscan so as to avoid resampling using points)

Appendix 9: Household survey instrument (Spanish)

ENCUESTA SOBRE SEGURIDAD ALIMENTARIA Y VULNERABILIDAD, Manabí, 2004 (Version 5) Responsable Andrew Farrow, University of East Anglia

1. Codigo de encuesta (ab/123) ____/_______	2. Nombre del encuestador (a) LA □ ND □ RC □ PV □	3. Fecha (dd/mm/aaaa) / / 2004
4. GPS Longitud: ______/______/______ E □ W □ 5. GPS Latitud: ______/______/______ N □ S □ 6. GPS Altura aproximada (sobre el nivel del mar): _____m		

Sobre la comunidad

7. Nombre de la Comunidad	8. Nombre de la Parroquia	9. Nombre del Canton
10.¿Usted vive en?	Zona plana □ Loma □	11.¿Usted vive en? Zona urbana □ Zona rural □
12. ¿Qué considera como lo mejor que tiene el lugar donde vive? ____ __________ ____ __________		
13. ¿Qué considera como lo peor que tiene el lugar donde vive? ____		

__________   ____   __________

Antecedentes

14. Nombres:	15. Apellidos:	16. Sexo: F □ M □

17. ¿Cuántas personas viven aquí? _________________	18. ¿Cuántos años llevan viviendo aquí? _________________
19. ¿Cuántos de los de aquí, generan un ingreso para la familia? Hombres: _____________________________ Mujeres: _____________________________	20. Tipo de vivienda: (a) Techo : Zinc □ Cady □ Losa □ Otros □ (b) Paredes: Cemento □ Ladrillo □ Madera □ Caña □ (c) Piso: Ceramica □ Cemento □ Madera □ Caña □ Tierra □

Bienestar

21. ¿Qué es lo que considera más importante para su bienestar?

Poner en orden de importancia (Numere de 1 a 10, siendo 1 el más importante y el 10 el de menor importancia).

	(a) Tener Usted y su familia buena salud
	(b) Poder superarse a través de una buena educación
	(c) Tener más / mejor tierra

	(d) Tener más / mejores animales (e) Disponer de buenos servicios públicos (agua, energía, alcantarillado, carretera, etc) (f) Tener una casa más grande / mejor (g) Tener más dinero (h) Tener seguridad de ingresos (i) Contar con ayuda de la familia y comunidad (j) Vivir en un buen ambiente social sin delincuencia

22. Detallar características de las personas que viven aquí y su Educación y Salud:

(1) Nombre de la persona	(2) Sexo	(3) Edad años	(4) Para >15, lee y escribe?	(5) Educación formal (nivel) **N**inguno **P**rimaria **S**ecundaria **T**écnico **U**niversitario	(6) Salud **B**ueno **R**egular **M**alo
a. Cabeza de familia	F □ M □		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □
b.	F □ M □		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □
c.	F □ M		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □

	□				
d.	F □ M □		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □
e.	F □ M □		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □
f.	F □ M □		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □
g.	F □ M □		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □
h.	F □ M □		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □
i.	F □ M □		S □ N □	N □ P □ S □ T □ U □	B □ R □ M □

Migración

23. ¿ Una persona quien ha vivido aquí se ha marchado a otro lugar fuera de la comunidad? S □ N □ (va a pregunta 26)
24. ¿Por qué salieron del lugar donde usted vive?

□ Porque aquí las cosas iban muy mal y no tuvieron otra opción más que irse □ Porque tuvieron una oferta de trabajo en otra parte □ Matrimonio □ Otra razón. ¿Cuál? ____ ____
25. Para aquellos que migran:

(1) Nombre de la persona	(2) Sexo	(3) ¿Cuando salieron? (año)	(4) Tipo de migración (**T**emporal, **P**ermanente)	(5) ¿Hacia donde?	(6) ¿Envía dinero? (S/N)
a.	F □ M □		T □ P □		S □ N □
b.	F □ M □		T □ P □		S □ N □
c.	F □ M □		T □ P □		S □ N □

26. ¿Si usted tuviera la opción, saldría del lugar donde vive? S □ N □

Condiciones biofísicas y amenazas naturales

27. ¿Perciben su casa o tierras como propensas a problemas ambientales o amenazas naturales?

S ¿Cuáles?

____

____

N ¿ Por qué no?

____

____

28. ¿Cuáles fueron las mayores crisis o eventos **naturales** que usted recuerda? Describirlas **en orden de importancia** en la tabla siguiente (siendo (a) el más importante).

(1) Evento natural	(2) ¿Cuándo pasó? (año)	(3) ¿Porqué importante?
(a)		
(b)		
(c)		

El fenómeno de El Niño de 1997/98

29. Durante las lluvias fuertes que acompañaron el fenómeno de El Niño de 1997/98, hubo en su comunidad:

- Inundaciones
- Deslaves / derrumbes / deslizamientos
- Ambos

☐ Ninguno

30. Si hubo inundaciones, **su hogar** o **su propiedad** fueron afectados por:	
	Muerte de familiares o amigos (nombre)
	Daños de la casa u otro edificio
	Pérdida total de casa u otro edificio
	Pérdida de cultivos por inundaciones
	Pérdida de productos agrícolas perecederos que no pudieron llevarse al mercado destino porque las vías de transporte estuvieron obstruidas o dañadas.
	Pérdida de animales
	Otros daños. ¿Cuáles? ____ ____ ____________________
	No hubo daños
31. Si hubo deslaves, **su hogar** o **su propiedad** fueron afectados por:	
	Muerte de familiares o amigos (nombre)
	Daños de la casa u otro edificio
	Pérdida total de casa u otro edificio
	Pérdida de cultivos por deslaves
	Pérdida de productos agrícolas perecederos porque las vías de transporte estuvieron obstruidas o dañadas
	Pérdida de animales
	Otros daños. ¿Cuáles? ____ ____ ____________________
	No hubo daños

Trabajo y El Niño

32. Si para usted, o las personas quien viven aquí hubo **trabajo** a pesar de las lluvias fuertes que acompañaron el fenómeno de El Niño de 1997/98: ☐ Hubo trabajo todo el tiempo ☐ No hubo trabajo todo el tiempo ☐ No hubo trabajo

Comida y El Niño

33. Si para usted, o las personas quien viven aquí hubo suficiente **comida** a pesar de las lluvias fuertes que acompañaron el fenómeno de El Niño de 1997/98: ☐ Hubo suficiente comida todo el tiempo (va a pregunta 36) ☐ Hubo meses de escasez de comida ☐ No hubo suficiente comida todo el tiempo
34. ¿Porque no hubo suficiente comida todo del tiempo o meses de escasez? ____ __________ ____ __________ ____ __________
35. ¿Que hicieron para conseguir alimentos? ____ ___________ ____ ___________ ____ __________

Enfermedades y El Niño

36. Usted, o sus familiares sufrieron de **enfermedades** asociadas con el fenómeno de El Niño de 1997/98:

S ☐

N ☐ (va a pregunta 38)

37. Cuando sus familiares sufrieron de enfermedades:

	Murió alguien (nombre)
	Se le impidió trabajar
	No paso nada

Ayuda y El Niño

38. Cuando usted, su propiedad, sus familiares o amigos sufrieron de daños o enfermedades asociadas con el fenómeno de El Niño de 1997/98, recibieron ayuda de:

	El Estado (nacional, provincial o cantonal)
	Familiares
	Grupos locales
	Amigos
	Organizaciones no-gubernamentales
	No recibieron ayuda
	No sufrieron

Bienestar y El Niño

39. Siente que el bienestar suyo y el de su familia es

□ Peor después de el fenómeno de El Niño de 1997/98. ¿Por qué?:

____

____

□ Igual después de el fenómeno de El Niño de 1997/98

□ Ha mejorado aún después de el fenómeno de El Niño de 1997/98. ¿Por qué?:

____

Prevención y El Niño

40. ¿Usted ha tomado medidas para prevenir daños asociados con el fenómeno de El Niño de 1997/98?

S □

N □ (va a pregunta 43)

41. ¿Cuales medidas ha tomado?

____

____

42. ¿Como se entero de esas medidas?

____

____

43. ¿Alguien más del lugar donde vive ha tomado medidas para prevenir daños asociados con el fenómeno de El Niño de 1997/98?

S □ N □ (va a pregunta 46)
44. ¿Cuales medidas ha tomado? ____ ____ ____
45. ¿Como se entero de esas medidas? ____ ____
46. ¿Ha existido algún **comité** de atención y prevención de desastres en la comunidad? S □ N □ En caso que sí, ¿Cuál? ____
47. ¿Esta comité esta funcionando ahora? S □ N □ En caso que sí, ¿Hace cuanto esta funcionando? ________________________________ En caso que no, ¿Hace cuanto dejo de funcionar? ____________________________________
48. ¿Existe algún **plan** de atención y emergencia en caso de algún desastre? S □ N □

En caso que sí, explicar ____ ____ _________________
49. ¿Existe algún programa de **prevención** de desastres? S □ N □ En caso que sí, explicar ____ ____ _________________
50. ¿Se realiza algún tipo de simulacro? S □ N □
51. ¿Pertenece a algún comité o grupo en la comunidad que atienda emergencias o desastres? S □ N □ En caso que sí ¿Cuál? ____ _________
52. ¿La familia o un individuo de la familia tiene algún rol o responsabilidad dentro de la comunidad? S □ N □ En caso que sí ¿Cuál? ____ _________

53. Si algo como el fenómeno de El Niño de 1997/98 ocurrieran de nuevo mencione hasta tres cosas que Usted haría

a. ____

b. ____

c. ____

Infraestructura y servicios

54. Hay acceso a **carretera** directo a su hogar

S □
N □

55. Cual es su calidad

B □ R □ M □

56. Hubo cambios después de El Niño de 1997/98 en la calidad de la carreterra

Mejor □ Igual □ Peor □

57. Cual es su modo de transporte normal

Carro □
Acemila □
Pié □

58. Cual es el tiempo a la población mas cercana donde se hace intercambio comercial:

(a)_________ horas (b)________ minutos

59. Hay suministro de **agua potable**

S □
N □

60. Cual es su calidad

B □ R □ M □

61. Hubo cambios después de El Niño de 1997/98 en el suministro y / o calidad de agua potable Mejor ☐ Igual ☐ Peor ☐	
62. Que tipo de acceso de agua potable hay Tuberia dentro de la casa ☐ Tuberia fuera de la casa ☐ Hay que ir al pozo ☐ Hay que ir a un Rió, Quebrada o Nacimiento ☐ Otro ☐	63. Cuanto tiempo se demora en la colecta del agua cada día: (a)_________ horas (b)________ minutos

64. Hay suministro de **energía eléctrica** S ☐ N ☐	65. Cual es su calidad B ☐ R ☐ M ☐
66. Hubo cambios después de El Niño de 1997/98 en el suministro y / o calidad de energía eléctrica Mejor ☐ Igual ☐ Peor ☐	

67. Hay **servicios sanitarios** S ☐ N ☐	68. Cual es su calidad B ☐ R ☐ M ☐

69. Hubo cambios después de El Niño de 1997/98 en la presencia y / o calidad de los servicios sanitarios Mejor ☐ Igual ☐ Peor ☐

70. Hay accesso a **servicios teléfonicos** S ☐ N ☐	71. Cual es su calidad B ☐ R ☐ M ☐
72. Hubo cambios después de El Niño de 1997/98 en la prestación y / o calidad de servicios teléfonicos Mejor ☐ Igual ☐ Peor ☐	
73. Cuanto tiempo se demora en llegar al teléfono más cercano ____________ horas ____________ minutos	

74. Hay accesso a **servicios de salud** S ☐ N ☐	75. Cual es su calidad B ☐ R ☐ M ☐
76. Hubo cambios después de El Niño de 1997/98 en la prestación y / o calidad de servicios de Salud Mejor ☐ Igual ☐ Peor ☐	
77. Cual es el Centro de Salud más cercano funcionando (nombre o lugar) ____ ____	78. Cuanto tiempo se demora en llegar al centro de salud en: (a) Carro (1)_____ horas (2)_____ minutos

	(b) Acemila (1)_____ horas (2)_____ minutos (c) a Pié (1)_____ horas (2)_____ minutos

Uso de la tierra

79. Ha habido cambios en la **tenencia** de la tierra en la comunidad? S □ ¿Cuáles? ____ N □
80. Especificar si en los últimos años trabajó en tierra **P**ropia, **A**lquilada, a **M**edias, como **J**ornalero, o en **N**inguna (a) Antes de el fenómeno de El Niño de 1997/98 P □ A □ M □ J □ N □ (b) Ahora P □ A □ M □ J □ N □
81. En relación con tenencia de la tierra se considera estar en una situación: □ más ventajosa hoy ¿Por qué? ____ □ igual que antes □ menos ventajosa hoy ¿Por qué? ____

82. Área total de la finca propia ahora ______ y antes ________del fenómeno de El Niño de 1997/98 Ha □ Cuadra □ Metro cuadrado □ Otro □
83. Determinar como es hoy el uso de la tierra en relación con antes de el fenómeno de El Niño de 1997/98 (a) Cultivos de ciclo corto Mayor cobertura □ Igual □ Menor □ No Sabe □ (b) Cultivos de ciclo largo Mayor cobertura □ Igual □ Menor □ No Sabe □ (c) Descanso Mayor cobertura □ Igual □ Menor □ No Sabe □ (d) Pasto Mayor cobertura □ Igual □ Menor □ No Sabe □ (e) Bosque Mayor cobertura □ Igual □ Menor □ No Sabe □ (f) No utilizable Mayor cobertura □ Igual □ Menor □ No Sabe □

Appendix 10: Key informant interview summaries

Interview 1: San Pablo Tarugo, Canuto district, catchment of river Tarugo
Saturday 24th January 2004

I conducted an informal interview with a young man who was processing cassava with his family. He said that for his family there were no ill effects during the 1997-98 El Niño phenomenon. They were able to harvest three consecutive crops of rice. The man said that there were landslides in his father's farm but that these did not overly inconvenience his father. He did say that some other people in the community had suffered, and that one man had been swept away with his horse and had died. People had problems selling their harvested crops and that the only access to the nearest market (Canuto) was a treacherous journey by raft. Much of the production was lost but some was stored although the price was highest at precisely the moment when the town was inaccessible.

Interview 2: Casagrande, Canuto district, catchment of river Tarugo
Sunday 25th January 2004

Prospero Moreira has lived all his life in the village of Casagrande and suffers from Parkinson's disease so his wife did most of the talking. The Moreiras have 10 children and innumerous grandchildren, many of them living in the same dwelling, the electricity lines do not reach the house but they have a small cassava processing plant (the chipper is fuelled by kerosene). During the 1997-98 El Niño phenomenon they recalled that they used a small raft to get to Canuto but normally they said that they felt closer to the cantonal capital of Chone, which is physically closer, but in a parallel valley. The family themselves did not consider that they had suffered during the last El Niño but they knew a case where a house had been entombed by a landslide and the children buried and the mother badly wounded.

Interview 3: San Elias, Canuto district, catchment of river Tarugo

Sunday 25th January 2004

Doña Marianita Vera is the local ‘catechist’ and wife of an important landlord; they donated land for the village of San Elias after it had been ‘invaded’ (squatted) by local people. Even though San Elias is only 4 kilometres from Casagrande the atmosphere was notably more suspicious. Marianita explained that this was because supposed technicians from the electricity company had arrived earlier in the month to try and get money from the residents. Despite this Marianita said that the thing she most disliked about San Elias was the state of the road and she would put up with increased crime if it meant that they could take out their products during the wet season. She also said that the community needed new accommodation for a local women’s artisan group. Regarding the 1997-98 El Niño phenomenon she at first said that there were no ill-effects and that the river Tarugo never rose too high. After giving the situation some thought she changed her idea and said that during the last El Niño there were serious problems in getting products to market. I asked her about organisations in San Elias and she told me that the village had recently formed a ‘rural security brigade’. The president of the local organisation of rural brigades had given a seminar in the village and the villagers had taken it from there. Marainita said that before the brigade was set up there were problems with drunkenness and anti-social behaviour from some villagers but that now these had been curbed. Various seminars have taken place in the village on a wide range of subjects but no one had ever given any advice about prevention measures for natural events. Doña Marianita commented that in the past the rains had been equally intense but that the river never rose so high or so rapidly. She put down the change to deforestation of the upper catchment, without tree cover more rain was converted to run-off and arriving more quickly in the channels.

Interview 4: Narciso, Chone district, catchment of river Chone
Monday 26th January 2004

The first interview was with two teachers in the village of Narciso close to Chone. This area is flat and the agriculture is of a different scale to that practised in the Tarugo valley.

According to the teachers all of the valley bottom is prone to flooding and was flooded during the last El Niño, there were also landslides in the hilly part of the village. This was no better and no worse than the El Niño of 1982-83, the school itself had been flooded but this was not a major concern for the teachers. They thought that the valley floor was probably more fertile than before but that it required different management techniques because there were now lots of rocks and that the fertile soil was below the rocky surface layer. They considered that trees like cocoa would be a good option because the roots are deep. The teachers considered the area to be *minifundia* in nature with no one having more than 100 hectares, the majority owning between 2 and 6 hectares. They blame the deforestation for both the droughts and the floods, but in general they were more concerned with droughts than with floods or landslides, it must be said that this interview took place during what should have been the wet season, in fact it had not rained for nearly a month. The teachers considered that the flooding and landslides affected rich and poor alike but that the poor inevitably suffered more.

Interview 5: Narciso, Chone district, catchment of river Chone
Monday 26th January 2004

The second interview was with Fabiola XXXX, a woman who lived 28 years in Narciso.
For Doña Fabiola the earthquake of 1998 was a far more frightening event than El Niño because it affected everyone and nobody had any warning nor knew if there would be aftershocks. During the 1997-98 El Niño phenomenon the whole of the valley floor flooded and the current was strong enough to take away the fence posts below the house that marked the limits of her land. With regard to sicknesses the most common were colds. Many wells in the area had turned ‘salobre’ (salty) but hers was still potable (after boiling). Fabiola lived on a hillside above the valley but was not too concerned with landslides because they had never affected her land or her house.

Interview 6: Narciso, Chone district, catchment of river Chone
Monday 26th January 2004

The third interview of the day was with Wilter Coppiano Limongi a large landowner who lives part of the time in Chone and the rest in the USA. Despite the comment of the teachers Wilter owned 200 hectares in the valley and grows plantain and papaya and raises cows. He lost nearly all of his plants of plantain in 1997-98 but was able to plant these again. He didn't lose any cows but some infrastructure such as milking barns and byres were destroyed. He was lucky enough to own land on the hillsides and moved the cows upslope when the rains arrived. When asked why he didn't have cocoa he explained that it took up to 5 years for cocoa to produce and that in the mean time there could be flooding again and he would lose the whole crop. Plantain in comparison took only 10 months to produce reducing the chances of losing money. In contrast to most other producers he doesn't worry about droughts because his fields are irrigated with water from wells on his land. He has not bought land even though there is some for sale in the area. He is actively reforesting his land and does not cut existing forests. However he is reforesting with a tree called Pachaco, a tree used mainly for timber rather than for protection.

Interview 7: La Chorrera, Canuto district, catchment of river Tarugo
Wednesday 28th January 2004

An interview was held with local trader Auxilio XXXX from La Chorrera, he mentions that the last El Niño was severe and that the water rose to a metre on a nearby building and that the people came running up the hill to seek refuge behind his shop. He didn't suffer because he had put a low concrete wall around the shop to protect it from floodwater and run-off from the road. He said that in a nearby hamlet (La Ribera) a whole hillside had collapsed burying a house and killing the three or four people who were inside. He said that the 1998 earthquake was frightening but didn't do any damage.

Interview 8: Chone, Chone district, catchment of river Chone
Wednesday 28th January 2004

An interview was held with Arq. Yolanda Muñoz of the Technical Secretariat of Cooperation who is responsible for the production of the Strategic development Plan for the Canton of Chone. She said that in the town of Chone the people are loathe to move away from their houses for fear of being robbed, instead they move their belongings up a floor and onto the roof. After the floods there was a lot of disease, especially dengue fever.

Appendix 11: Association between short and long-term impacts of the 1997-98 El Niño event

Contingency table of the short-term direct impacts of floods which were the result of the 1997-98 El Niño event and the judgments of respondents of their current well-being compared to the situation before the 1997-98 El Niño event

			Do you feel that your well-being and that of your household is…			
Floods responsible for…			Worse since the 1997/98 El Niño	The same since the 1997/98 El Niño	Better since the 1997/98 El Niño	Total
…death of a member of family or friend	No	Count	72	89	37	198
		Expected	69.5	92.3	36.2	
	Yes	Count	1	8	1	10
		Expected	3.5	4.7	1.8	
…damages to the house or other buildings	No	Count	50	72	26	148
		Expected	51.9	69	27	
	Yes	Count	23	25	12	60
		Expected	21.1	28	11	
…total loss of house or other building	No	Count	69	92	34	195
		Expected	68.4	90.9	35.6	
	Yes	Count	4	5	4	13
		Expected	4.6	6.1	2.4	
…loss of crops due to damage in the field	No	Count	39	63	25	127
		Expected	44.6	59.2	23.2	
	Yes	Count	34	34	13	81
		Expected	28.4	37.8	14.8	
…post-harvest damage due to lack of access to markets	No	Count	68	88	35	191
		Expected	67.0	89.1	34.9	
	Yes	Count	5	9	3	17
		Expected	6.0	7.9	3.1	
…loss of animals	No	Count	51	83	30	164
		Expected	57.6	76.5	30	

	Yes	Count	22	14	8	44
		Expected	15.4	20.5	8	
…other damages	No	Count	70	91	37	198
		Expected	69.5	92.3	36.2	
	Yes	Count	3	6	1	10
		Expected	3.5	4.7	1.8	
…all/any damages	No	Count	19	28	16	63
		Expected	22.1	29.4	11.5	
	Yes	Count	54	69	22	145
		Expected	50.9	67.6	26.5	
Total		Count	73	97	38	208

Contingency table of the short-term direct impacts of landslides which were the result of the 1997-98 El Niño event and the judgments of respondents of their current well-being compared to the situation before the 1997-98 El Niño event

Landslides			Do you feel that your well-being and that of your household is…			
			Worse since the 1997/98 El Niño	The same since the 1997/98 El Niño	Better since the 1997/98 El Niño	Total
death of a member of family or friend	No	Count	72	93	38	203
		Expected	71.2	94.7	37.1	
	Yes	Count	1	4	0	5
		Expected	1.8	2.3	0.9	
damages to the house or other buildings	No	Count	55	84	31	170
		Expected	59.7	79.3	31.1	
	Yes	Count	18	13	7	38
		Expected	13.3	17.7	6.9	
total loss of house or other building	No	Count	67	93	33	193
		Expected	67.7	90	35.3	
	Yes	Count	6	4	5	15
		Expected	5.3	7	2.7	
loss of crops due to	No	Count	29	54	26	109

damage in the field		Expected	38.3	50.8	19.9	
	Yes	Count	44	43	12	99
		Expected	34.7	46.2	18.1	
post-harvest damage due to lack of access to markets	No	Count	60	87	37	184
		Expected	64.6	85.8	33.6	
	Yes	Count	13	10	1	24
		Expected	8.4	11.2	4.4	
loss of animals	No	Count	51	86	36	173
		Expected	60.7	80.7	31.6	
	Yes	Count	22	11	2	35
		Expected	12.3	16.3	6.4	
Other damages	No	Count	66	89	38	193
		Expected	67.7	90.0	35.3	
	Yes	Count	7	8	0	15
		Expected	5.3	7.0	2.7	
No damages	No	Count	59	60	17	136
		Expected	47.7	63.4	24.8	
	Yes	Count	14	37	21	72
		Expected	25.3	33.6	13.2	
Total		Count	73	97	38	208

References

Abad-Franch, F., and Aguilar, H.M., 2003. *Control de la Enfermedad de Chagas en el Ecuador*. OPS/OMS – Ministerio de Salud Pública del Ecuador. Quito, Ecuador, December 2002 - February 2003. 146pp. Available at: http://www.opsecu.org/bevestre/revistas/publicaciones/OPS.pdf

Abrahams, A.D., Parsons, A.J., and Wainwright, J., 1994. Resistance to overland flow on semiarid grassland and shrubland hillslopes, Walnut Gulch, southern Arizona. *Journal of Hydrology*, 156: 431-446

Adger, W. N., 1999. Social Vulnerability to Climate Change and Extremes in Coastal Vietnam. *World Development*, 27: 249-269.

Adger, W.N., 2003. Social Capital, Collective Action, and Adaptation to Climate Change. *Economic Geography*, 79(4): 387–404

Adger, W.N., and Vincent, K., 2005. Uncertainty in adaptive capacity. *Comptes Rendus Geosciences*, 337: 399-410.

African Union, 2004. *Programme of Action Proposal for the Implementation of the Africa Regional Strategy for Disaster Risk Reduction*. Addis Ababa, Ethiopia, African Union. Available at: http://www.africa-union.org/Agriculture/Disaster_Risk_Reduction/Programme_of_Action.pdf

Alderman, H., Babita, M., Demombynes, G., Makhatha, N., and Özler, B., 2003. How Low Can You Go? Combining Census and Survey Data for Mapping Poverty in South Africa. *Journal of African Economies*, 11 (2):169-200.

Alcantara-Ayala, I., 2004. Hazard assessment of rainfall-induced landsliding in Mexico. *Geomorphology*, 61: 19–40

Alianza Jatun Sacha – CDC Ecuador, 2003. *Almanaque Electrónico Ecuatoriano*. Quito, Ecuador.

Alkire S., 2002. Dimensions of human development, *World Development*, 30 (2): 181-205

Alwang, J., Siegel, P.B. and Jorgensen, S.L., 2001. *Vulnerability: A View from Different Disciplines*. 0115, World Bank, Washington, D.C.

Amudavi, D., 2005. *Exploring the Effects of Farmer Community Group Participation on Rural Livelihoods*. Policy Brief, February 2005, SAGA, Cornell University. Available at http://www.einaudi.cornell.edu/files/calendar/4568/Amudavi_policy_brief.pdf

Anand P., Hunter G., and Smith R., 2005. Capabilities and well-being: Evidence based on the Sen-Nussbaum approach to welfare. *Social Indicators Research*, 74 (1): 9-55

Anand, S., and C. Harris. 1989. "Food and Standard of Living: An Analysis on Sri Lankan Data." in Dreze, J.P., and A.K. Sen ed., 1991. *The Political Economy of Hunger Vol 1:Entitlement and Well-Being*. Oxford: Oxford University Press.

Andolina, R., 2003. The Sovereign and its Shadow: Constituent Assembly and Indigenous Movement in Ecuador. *Journal of Latin American Studies*, 35: 721–750.

Anyamba, A., Tucker, C. J. and Mahoney, R., 2002. From El Niño to La Niña: Vegetation Response Patterns over East and Southern Africa during the 1997-2000 Period. *Journal of Climate*, 15: 3096-3103.

Artan, G., Gadain, H., Smith, J.L., Asante, K., Bandaragoda, C.J., and Verdin, J.P., 2007. Adequacy of satellite derived rainfall data for stream flow modeling. *Natural Hazards*, 43: 167–185

Ashley, C., and Carney, D., 1999. *Sustainable Livelihoods: Lessons from Early Experience*. London: DFID. Available at: http://www.livelihoods.org/static/cashley_NN16.html

Asociación COPADE – ICA, n.d. *Tables of precipitation compiled for project: Control de Inundaciones de la ciudad de Chone*. Sample available at: http://www.ambiente.gov.ec/userfiles/222/file/DIAGNOSTICO%20AMBIENTAL%20DE%20LOS%20RIOS%20CHONE%20Y%20PORTOVIEJO/Capitulo%205.pdf

Atkinson, A.B., 1989. *Poverty and Social Security*. Hemel Hempstead, Harvester Wheatsheaf.

Baez, J. E. and Mason, A., 2008. *Dealing with Climate Change: Household Risk Management and Adaptation in Latin America*. SSRN eLibrary. Available at http://ssrn.com/paper=1320666

Baeza, C., and Corominas, J., 2001. Assessment of Shallow Landslide Susceptibility by Means of Multivariate Statistical Techniques. *Earth Surface Processes and Landforms*, 26: 1251-1263.

Baeza, C. and Packard, T., 2006. *Beyond survival: protecting households from health shocks in Latin America*, Washington DC, World Bank.

Bahremand, A., de Smedt, F., Corluy, J., Liu, Y.B., Poorova, J., Velcicka, L., and Kunikova, E., 2007. WetSpa Model Application for Assessing Reforestation Impacts on Floods in Margecany–Hornad Watershed, Slovakia. *Water Resources Management*, 21, (8), 1373-1391

Balk, D., Pozzi, F., Yetman, G., Deichmann, U., and Nelson, A., 2005. The Distribution of People and the Dimension of Place: Methodologies to Improve the Global Estimation of Urban Extents. *Proceedings of the Urban Remote Sensing Conference*, Tempe, Arizona, April 2005. Available at: http://www.iussp.org/Activities/wgc-urb/balk.pdf

Barbieri, A.F., 2005. *People, Land and Context: Multi-scale Dimensions of Population Mobility in the Ecuadorian Amazon*. Ph.D, University of North Carolina at Chapel Hill, pp204; AAT 3190217. Available at:

Barrett, C.B., 1999. *On Vulnerability, Asset Poverty and Subsidiarity*. Ford/ Rockefeller Foundations Seminar Series session "Managing Variability and Shocks within the Agro-Food System.

Barrett, C., 2001. Integrating Qualitative and Quantitative Approaches: Lessons from the Pastoral Risk Management Project, pp. 56-60 in Kanbur, R, Ed., *Qual-Quant - Qualitative and Quantitative Poverty Appraisal: Complementarities, Tensions and the Way Forward*. Cornell University, March 15-16, 2001.

Barrett, C. B., Reardon, T. and Webb, P., 2001. Nonfarm Income Diversification and Household Livelihood Strategies in Rural Africa: Concepts, Dynamics, and Policy Implications. *Food Policy*, 26, 315-331.

Basabe., P, and Bonnard, C., 2002. Instability management in Ecuador - from policy to practice. McInnes, R.G., and Jakeways, J., eds. *Instability Planning and Management*. Isle of Wight, Thomas Telford:659-70. Available at: http://cooperation.epfl.ch/webdav/site/cooperation/shared/publications/Instability_management_Ecuador_Basabe-Bonnard.pdf

Bassett, D., Pettit, A., Anderton, C., and Grace, P., 2007. *Scottish Flood Defence Asset Database Final Report*, JBA Consulting, ISBN 978 0 7559 1563 7. Available at: http://www.scotland.gov.uk/Publications/2007/08/20111904/0

Basu, K., Narayan, A., and Ravallion, M., 2001. Is Knowledge Shared Within Households?, *Labour Economics*, 8 (6): 649-665.

Baulch, B., and Hoddinott, J., 2000. *Economic Mobility and Poverty Dynamics in Developing Countries*. Taylor and Francis. p184, ISBN 0714681547

Bebbington, A., and Perreault,T., 1999. Social Capital, Development, and Access to Resources in Highland Ecuador. *Economic Geography*, 75 (4): 395-418.

Bell, G.D. and Halpert, M.S., 1998. Climate Assessment for 1997. *Bulletin of the American Meteorological Society*, 79: 1014–1014.

Bell R., Hoffmann, T., and Meyer, N., 2007. Transient perturbation of fluvial systems by landsliding: Examples from the Swabian Alb (SW-Germany). *Geophysical Research Abstracts*, 9: 10677.

Benson, T., Chamberlin, J., and Rhinehart, I., 2005. An investigation of the spatial determinants of the local prevalence of poverty in rural Malawi. *Food Policy*, 2005, 30 (5-6): 532-550

Bendix, A., and Bendix, J., 2006. Heavy rainfall episodes in Ecuador during El Niño events and associated regional atmospheric circulation and SST patterns. *Advances in Geosciences*, 6: 43–49

Bendix, A., Bendix, J., Gämmerler, S., Reudenbach C. and Weise, S., 2002. The El Niño 1997/98 as seen from Space - Rainfall Retrieval and Investigation of Rainfall Dynamics with GOES-8 and TRMM Data. *Proceedings the 2002 EUMETSAT Meteor. Satellite Conf.*, Dublin, Ireland 02-06 Sept. 2002, EUM P 36

Berman, S., 1997. Civil Society and the Collapse of the Weimar Republic.*World Politics*, 49 (April): 401-29.

Beven, K.J., and Kirkby, M.J., 1979. A Physically Based, Variable Contributing Area Model of Basin Hydrology. *Hydrological Sciences Bulletin*, 24 (1): 43-69.

Bezemer D.J., and Lerman, Z., 2003. *Rural Livelihoods in Armenia*. Discussion Paper No. 4.03, May 2003. The Center for Agricultural Economic Research, and the Department of Agricultural Economics and Management. The Hebrew University of Jerusalem, Israel. Available at: http://departments.agri.huji.ac.il/economics/lerman-armenia.pdf

Bhargava A.; and Ravallion, M., 1993. Does Household Consumption Behave as a Martingale? A Test for Rural South India. *The Review of Economics and Statistics*, 75 (3): 500-504.

Bjerknes, J.,1969. Atmospheric Teleconnections from the Equatorial Pacific. *Monthly Weather Review*, 97: 163-172.

Blaikie, P., Cameron, J. and Seddon, D., 1977. *Centre, Periphery and Access in West Central Nepal: Approaches to Social and Spatial Relations of Inequality*. Norwich, UEA.

Blaikie, P., Cannon, T., Davis, I. and Wisner, B., 1994. *At Risk: Natural hazards, people's vulnerability, and disasters*. Routledge, London and New York, 284 pp.

Boardman, J., Evans, R. and Ford, J., 2003. Muddy floods on the South Downs, southern England: problem and responses. *Environmental Science and Policy*, 6: 69.

van der Bolt, F.J.E., and Immerzeel, W.W., 2002. Regional Flood Risk Assessment By Combining Hydrological Modelling and GIS Technology, *EGS XXVII General Assembly*, Nice, 21-26 April 2002

Boltvinik, 1990. *Pobreza y necesidades básicas, proyecto regional para la superación de la pobreza*. UNDP, Caracas, Venezuela.

Boudreau, T., 2007. *Putting the 'ability' back in Vulnerability: Food Security Early Warning Systems and The Livelihoods Integration Unit in Ethiopia*. F.E.G. Consulting. Available at: http://www.feg-consulting.com/resource/reports/Boudreau%20Putting%20the%20Ability%20Back%20in%20Vulnerability.pdf

Bourguignon, F., 2001. Qualitative and quantitative approaches to poverty analysis: two pictures of the same mountain? In: *Contributions to "Qual-Quant. Qualitative* *and quantitative poverty appraisal: complementarities, tensions and the way forward"*, 44-46. Cornell University, March 15-16, 2001.

Bradshaw, C.J.A., Sodhi, N.S., Peh, K.S.H., and. Brook, B.W., 2007. Global evidence that deforestation amplifies flood risk and severity in the developing world. *Global Change Biology*, 13: 2379–2395.

Bratti, M., Bucci, A. and Moretti, E., 2001. Demographic Trends, Human Capital and Economic Growth in Developing Countries: Theory and Evidence, Policy Modeling for European and Global Issues. University of Ancona, Warwick University, University of Bologna, Catholic University of Louvain, Brussels. Available at: http://www.ecomod.net/conferences/ecomod2001/papers.htm

Braud, I., Vich A.I.J., Zuluaga, J., Fornero, L., and Pedrani A., 2001. Vegetation influence on runoff and sediment yield in the Andes region: observation and modelling. *Journal of Hydrology*, 254 (1-4): 124-144

Brenning, A., 2005. Spatial prediction models for landslide hazards: review, comparison and evaluation. *Natural Hazards and Earth System Sciences*, 5: 853–862.

Brooks, N., Adger, W.N. and Kelly, P.M., 2005. The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global Environmental Change Part A*, 15, 151.

Bryceson, D., Bradbury, A., and Bradbury, T., 2006. *Dissecting Rural Roads' Impact on Mobility in Africa and Asia*. African Studies Centre, Oxford, and TRL, Crowthorne, UK. March 2006

Buckland, J. and Rahman, M., 1999. Community-based Disaster Management during the 1997 Red River Flood in Canada. *Disasters*, 23(2): 174-191.

Burton, I., Kates, R.W. and White, G.F., 1993. *The Environment as Hazard*. Guilford Press, New York, 290 pp.

Calero, C., Bedi, A. S. and Sparrow, R., 2009. Remittances, Liquidity Constraints and Human Capital Investments in Ecuador. *World Development*, 37, 1143.

Cameron, J. D., 2005. Municipal Democratisation in Rural Latin America: Methodological Insights from Ecuador. *Bulletin of Latin American Research*, 24: 367-390.

Cane, M. A., 1983. Oceanographic Events During El Niño. *Science*, 222: 1189-1195.

Cannon, T., 2008. *Reducing People's Vulnerability to Natural Hazards: Communities and Resilience*. Research Paper 2008/34, UNU-WIDER.

Cannon, T., Twigg, J. and Rowell, J., 2003. *Social Vulnerability, Sustainable Livelihoods and Disasters*. Chatham, Natural Resources Institute.

Cardoso, M.R., Cousens, S.N., de Góes Siqueira, L.F., Alves, F.M. and D'Angelo, L.A., 2004. Crowding: risk factor or protective factor for lower respiratory disease in young children?. *BMC Public Health*, 4: 19

Carney, D., 2002. *Sustainable Livelihoods Approaches: Progress and Possibilities for Change*. London: DFID. Available at: http://www.livelihoods.org/static/dcarney_NN156.html

Carney, D., 1998. Implementing the sustainable Rural Livelihoods Approach. In: Carney, D., ed. *Sustainable Rural Livelihoods: What Contribution Cane We Make?*, Overseas Development Institute, London pp3-23.

Castellanos, E., 2005. Processing SRTM DEM Data for National Landslide Hazard Assessment. *VI Congreso De Geología (Geologia´2005), Simposio de Sismicidad y Riesgos Geológicos. Primera Convención Cubana de Ciencias de la Tierra, Geociencias´2005*, La Habana, 5th-8th April 2005.

Cavendish, W., 2000. Empirical Regularities in the Poverty-Environment Relationship of Rural Households: Evidence from Zimbabwe. *World Development*, 28(11): 1979-2003.

Central Intelligence Agency, 2009. *The World Factbook 2009*. Washington, DC. Available at: https://www.cia.gov/library/publications/the-world-factbook/index.html

Centre for Research on the Epidemiology of Disasters (CRED), 2002. *Emergency Events Database EM-DAT*. Centre for Research on the Epidemiology of Disasters. Available at: http://www.emdat.be/

Cerrutti, M., and Bertoncello, R., 2003. Urbanization and Internal Migration Patterns in Latin America. *Conference on African Migration in Comparative Perspective*, Johannesburg, South Africa, 4th - 7th June, 2003.

Chacaltana, J., 2002. *Social Funds and the Challenge of Social Protection for the Poor in Latin America*. Center for Development Studies, Asian Development Bank. Availabe at: http://www.adb.org/Documents/Events/2002/SocialProtection/chacaltana_presentation.pdf

Chakraborty, S., and Das, M., 2005. Mortality, Human Capital and Persistent Inequality, *Journal of Economic Growth*, 10: 159–192.

Chambers, R., 1989. *Vulnerability: How the Poor Cope*. IDS Bulletin, 20 (2).

Chambers, R., and Conway, G., 1991. *Sustainable rural livelihoods: practical concepts for the 21st century*. IDS Discussion Paper 296. Brighton, IDS. Available at: http://www.livelihoods.org/static/rchambers_NN13.html

Chang, M., 2006. *Forest Hydrology: An Introduction to Water and Forests*. Boca Raton, FL, CRC Press.

Charvériat, C., 2000. *Natural Disasters in Latin America and the Caribbean: An Overview of Risk*. New York, Inter-American Development Bank.

Chaudhuri, S., Jalan, J., and Suryahadi, A., 2002. *Assessing Household Vulnerability to Poverty from Cross-sectional Data: A Methodology and Estimates from Indonesia*. 0102-52, New York, Department of Economics, Columbia University.

Chaudhuri, S., and Ravallion, M., 1994. How Well Do Static Welfare Indicators Identify theChronically Poor?, *Journal of Public Economics*, 53: 367-394.

Christiaensen, L.J. and Subbarao, K., 2001. *Towards an Understanding of Vulnerability in Rural Kenya*, World Bank.

Coleman, J.S., 1988. Social Capital in the Creation of Human Capital. *American Journal of Sociology*, 94, 95-120.

Collins English Dictionary Online, 2010. HarperCollins. Accessed 23rd July 2010. http://www.collinslanguage.com

Comisión Económica para América Latina y el Caribe (CEPAL) 1998. *Ecuador: Evaluación de los efectos socio-económicos del fenómeno de El Niño en 1997-8*, Santiago de Chile, Comisión Económica para América Latina y el Caribe (LC/R.1822 y LC/MEX/R.657, 22 June 1998)

Comisión Económica para América Latina y el Caribe (CEPAL), 1999. *Estudio Económico de América Latina y el Caribe 1998-1999*, LC/G.2056-P/E, CEPAL, Santiago de Chile, ISBN: 92-1-321502-9, 364 pp

Connor, R. F., and Hiroki, K., 2005. Development of a method for assessing flood vulnerability. *Water Science and Technology*, 51: 61-67.

Coppin, N., and Richards, I., 1990. *Use of Vegetation in Civil Engineering*. London, Butterworths.

Corbett, J., 1988. Famine and Household Coping Strategies. *World Development*, 16: 1099-1112.

Corporación Andina de Fomento (CAF), 2000. *Las lecciones de El Niño: Memorias del Fenómeno El Niño 1997 - 1998 : Retos y propuestas para la Región Andina : Ecuador*. Caracas, Venezuela, CAF, October 2000.

Cook, S, Johnson, N, Swallow, B, Ravnburg, H, Beaulieu, N, Mulligan, M, Schreier, H, Valentin, C, Wani, S.P., Penning-de Vries, F, Sanz, N, Gottriet, V, and Westermann, O, 2002. *Multiple Use of Upper Catchments: Toward a Research Agenda for Subtheme Two of the Challenge Program on Water and Food*. Challenge Program on Water and Food Background Paper 2. Available at: http://www.iwmi.cgiar.org/challenge-program/pdf/paper2.pdf

Couto, P., 2003. Assessing the accuracy of spatial simulation models. *Ecological Modelling*, 167(1-2): 191-198

Datt, G. and Jolliffe, D., 1999. *Determinants of Poverty in Egypt: 1997*. Washington, D.C., Food Consumption and Nutrition Division, International Food Policy Research Institute.

Dattilo G., and Spezzano, G., 2003. Simulation of a cellular landslide model with CAMELOT on high performance computers. *Parallel Computing*, 29: 1403–1418

Davis, B. and Stampini, M., 2002. *Pathways towards prosperity in rural Nicaragua; or why households drop in and out of poverty, and some policy suggestions on how to keep them out.* FAO and Scuola Sant'Anna, Pisa. Available at: ftp://ftp.fao.org/docrep/fao/007/ae031e/ae031e00.pdf

Davis, B., and Stampini, M., 2003. Pathways towards prosperity in Nicaragua: an analysis of panel households in the 1998 and 2001 LSMS surveys. Annex 7, *Nicaragua Poverty Update*, February 2003. Available at: http://wbln0018.worldbank.org/LAC/LACInfoClient.nsf/9b5746666d690c46852567

3600834bcd/31a78860d493b7d685256e3900647139/$FILE/Nicaragua%20Poverty%20Asessm%20Annex-7.pdf

Deaton, A., 1997. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. Baltimore, MD, World Bank, Johns Hopkins University Press.

Deaton, A., and Zaidi, S., 2001.*Guidelines for constructing consumption aggregates for welfare analysis.* LSMS Working Paper 135, Washington D.C., World Bank.

Demoraes, F., and D'Ercole, R., 2001. *Mapas de Amenazas, Vulnerabilidad y Capacidades en el Ecuador: Los desastres, un reto para el desarrollo*. COOPI, Oxfam International, SIISE. August, 2001, Quito, Ecuador.

Department for International Development (DFID), 2000. *Sustainable Livelihoods Guidance Sheets*, London, UK Govt. Department for International Development.

D'Ercole, R., 2005. *Criterios de reflexión por la determinación de prioridades para la reducción de los riesgos en el Ecuador (preparación del plan IV DIPECHO).* DIPECHO, 3rd-5th May 2005, Quito, Ecuador, pp179

Dercon, S., Hoddinott, J. and Woldehanna, T., 2005. Consumption and shocks in 15 Ethiopian Villages, 1999-2004. *Journal of African Economies*, 14: 559-585.

DesInventar, 2004. Data available from: http://www.desinventar.org/

Devereux, S., Baulch, B., Hussein, K., Shoham, J., Sida, H. and Wilcock, D., 2004. *Improving the Analysis of Food Insecurity. Food Insecurity Measurement, Livelihoods Approaches and Policy: Applications in FIVIMS*. Available at: http://www.ipcinfo.org/attachments/Devereux_FIVIMS_paper.pdf

Diario Hoy, 2008. Defensa Civil es eliminada mediante Decreto Ejecutivo. *Diario HOY*. Quito. Available at: http://www.hoy.com.ec/noticias-ecuador/defensa-civil-es-eliminada-mediante-decreto-ejecutivo-296244-296244.html

Diekman, S.T., Kearney, S.P., O'Neil, M.E. and Mack, K.A., 2007. Qualitative study of homeowners' emergency preparedness: experiences, perceptions, and practices. *Prehosp Disaster Med*, 22, 494-501.

Diener, E., Suh, E.M., Lucas, R.E., and Smith, H.L., 1999. Subjective well-being: Three decades of progress. *Psychological Bulletin*, 125 (2): 276-302

Dikau, R. and Glade, T., 2003. Nationale Gefahrenhinweiskarte gravitativer Massenbewegungen. *Nationalatlas Bundesrepublik Deutschland*. Heidelberg.

Dirección Nacional de Defensa Civil (DNDC), 1997. *Plan de Contingencia para enfrentar el Fenómeno de El Niño* (mimeo). Quito, Ecuador; July 1997

Dirección Nacional de Defensa Civil (DNDC), 2002. *Informe Final del Desarrollo, Efectos e Incidencias del Fenómeno "El Niño" 1997-1998*. Quito, Ecuador. Unpublished, accessed April 2002.

Dirección Nacional de Defensa Civil (DNDC), 2003, *Zonificación de Amenazas por Terrenos Inestables, Flujos de Lodo e Inundaciones en Montecristi, Tosagua Y Charapotó.* Departamento Técnico, Not Published, received August 2003

Dobson, J.E., Bright, E.A., Coleman, P.R., Durfee, R.C., and Worley, B.A., 2000. LandScan: A Global Population Database for Estimating Populations at Risk. *Photogrammetric Engineering and Remote Sensing*. 66(7): 849-857

Dow, K., 1992. Exploring differences in our common future(s): the meaning of vulnerability to global environmental change. *Geoforum*, 23 (3): 417-436.

Drèze, J., and Saran, M., 1995. Primary Education and Economic Development in China and India : Overview and Two Case Studies. In. Basu, K., Pattanaik P. K., and Suzumura K., eds. *Choice, Welfare and Development*. Oxford, Clarendon Press.

Drèze, J. and Sen, A., 1989. *Hunger and Public Action*, Oxford, Clarendon Press.

Duncan, C., Jones, K., and Moon, G., 1996. Health-Related Behaviour in Context: A Multilevel Modelling Approach. *Social Science and Medicine*, 42 (6): 817-830

Durlauf, S.N., 2002. On the Empirics of Social Capital. *Economic Journal*, 112 (483): 459-479

Dutta, D. and Herath, S., 2002. GIS based Mathematical Model for Flood Disaster Response. *US-Japan 2nd Workshop on Comparative Study on Urban Disaster Management*, Port Island, Kobe, Japan. Available at: http://www.drs.dpri.kyoto-u.ac.jp/us-japan/cd-2/DushamantaDutta.pdf

Eakin, H., 2005. Institutional Change, Climate Risk, and Rural Vulnerability: Cases from Central Mexico. *World Development*, 33 (11): 1923–1938.

Eakin, H., and Bojórquez-Tapia, L.A., 2008. Insights into the composition of household vulnerability from multicriteria decision analysis. *Global Environmental Change*, 18**:** 112.

EcoCiencia, 2001. *Parroquias del Ecuador*. Digital dataset provided by EcoCiencia.

Elad, R.L., Houston, J.E., Keeler, A. and Baker, D., 1998. *Labor Productivity Within the African Agricultural Household: The Household Production Model Revisited*. FS 98-19, University of Georgia, FAO, Athens, GA.

Elbers, C., Lanjouw, J.O., Lanjouw, P., and Leite P.G., 2001. *Poverty and Inequality in Brazil: New Estimates from Combined PPV-PNAD Data*. Unpublished Manuscript, Washington DC, World Bank.

Elbers, C., Lanjouw, J.O., and Lanjouw, P., 2003. Micro-Level Estimation of Poverty and Inequality, *Econometrica*, 71 (1): 355-364.

Ellis, F., 1999. Rural Livelihood Diversity in Developing Countries: Evidence and Policy Implications. *Natural Resource Perspectives*, 40, April 1999. Overseas Development Institute, London, UK. Available at: http://www.odi.org.uk/nrp/40.html

Environmental Systems Research Institute (ESRI), 1992. *ArcWorld* (CD-ROM), Redlands, CA

Eriksen, S., and Kelly, P., 2007. Developing Credible Vulnerability Indicators for Climate Adaptation Policy Assessment. *Mitigation and Adaptation Strategies for Global Change*, 12: 495.

Escobal, J., and Torero, M., 2005. Measuring the Impact of Asset Complementarities: The Case of Rural Peru. *Cuadernos De Economía*, 42 (Mayo) 137-164. Available at: http://www.scielo.cl/pdf/cecon/v42n125/art07.pdf

Escuela Politécnica Nacional (EPN) and Dirección Nacional de Defensa Civil (DNDC), 2000. *Zonificación de Peligros Sismogeotécnicos, por Deslizamientos y Fenómenos Hidrometeorológicos en la Ciudad de Bahía de Caráquez*. Quito, February 2000.

Espinosa, P. and Garrett, P., 1987. The relevance of gender in farming systems research: Experiences in Ecuador. *Agricultural Administration and Extension*, 26: 101.

Esteban, J., Aguirre, C., Flores, A., Strauss, W., Angles, R., and Mas-Coma, S., 1998. High Cryptosporidium Prevalences in Healthy Aymara Children from the Northern Bolivian Altiplano. *American Journal of Tropical Medicine and Hygiene*, 58(1): 50–55

Eyben, R., 1998. *Poverty and Social Exclusion: North-South Links*. ODI, March 1998. Available at: http://www.odi.org.uk/events/archive/eyben.html.

Fafchamps, M. and Minten, B., 2001. Social Capital and Agricultural Trade. *American Journal of Agricultural Economics*, 83(3): 680-685.

Fagen, P.W., 2008. *Natural disasters in Latin America and the Caribbean: national, regional and international interactions. A regional case study on the role of the affected state in humanitarian action*. London, Overseas Development Institute.

Farrow, A., Hyman, G., Larrea, C., and Pérez, S.A., 2002. *Informe del taller sobre el Proyecto de Mejoramiento de Métodos de Análisis Espacial de la Pobreza y Seguridad Alimentaria en el Ecuador, 19-20 de Junio, 2002*. Quito. Report available from:
http://www.ecuamapalimentaria.info/downloads/InformeTallerQuitoJunio2002.pdf

Farrow, A., Larrea, C., Hyman, G., and Lema, G., 2005. Exploring the spatial variation of food poverty in Ecuador. *Food Policy*, 30 (5-6), 510-531.

Farrow, A. and Nelson, A., 2001. *Accessibility Modelling in ArcView 3: An extension for computing travel time and market catchment information*. Software manual, CIAT, Cali, Colombia. Available at: www.ciat.cgiar.org/access/pdf/ciat_access.pdf ,

Faust, J., Von der Goltz, N., and Schloms, M., 2007. Promoting subsidiarity-oriented decentralization in fragmented polities – some lessons from Ecuador. In Altenburg, T., ed. *From Project to Policy Reform: Experiences of German Development Cooperation*. Bonn, Deutsches Institut für Entwicklungspolitik.

Feres, J.C., and Mancero, X, 2001. El método de las necesidades básicas insatisfechas (NBI) y sus aplicaciones en América Latina. *Serie: Estudios estadísticos y prospectivos*, No. 7. United Nations Economic Commission for Latin America and the Caribbean, Santiago de Chile. Available at:
http://www.eclac.cl/publicaciones/xml/4/6564/lcl19491e.pdf

Ferriss A.L., 2000. The quality of life among US states. *Social Indicators Research*, 49 (1): 1-23

FEWS, 2002. *FEWS NET - Red de Alerta Temprana Contra la Inseguridad Alimentaria, Centroamérica*.

Fischer, S., 2000. Ecuador and the IMF. *Hoover Institution Conference on Currency Unions*, Palo Alto, California, May 19, 2000. Available at: http://imf.org/external/np/speeches/2000/051900.htm

Foody, G., 2006. What is the difference between two maps? A remote senser's view. *Journal of Geographical Systems*, 8: 119-130.

Foster, A., 2002. Demographic Analysis of Community, Cohort, and Panel Data from Low-Income Countries: Methodological Issues. In Durrant, V. L. and Menken, J. (Eds.) *Leveraging Longitudinal Data in Developing Countries: Report of a Workshop.* National Research Council.

Foster, J.E., Greer, J., and Thorbecke, E., 1984. A Class of Decomposable Poverty Indices. *Econometrica*, 52(3): 761-766.

Fotso, J.C., and Kuate, D.B., 2006. Household and Community Socioeconomic Influences on Early Childhood Malnutrition in Africa. *Journal of Biosocial Science*, 38: 289–313

Freeman, L.C., Kimball Romney, A., and Freeman, S., 1987. Cognitive Structure and Informant Accuracy. *American Anthropologist*, 89(2): 310-325.

Fritz, S. and See, L., 2008. Identifying and quantifying uncertainty and spatial disagreement in the comparison of Global Land Cover for different applications. *Global Change Biology*, 14: 1057-1075.

Fukuyama, F. 1995. *Trust: The Social Values and the Creation of Prosperity*. New York, Free Press, 1995.

Furstenberg, F. and Hughes, M., 1995. Social capital and successful development among at-risk youth. *Journal of Marriage and the Family*, 57: 580-592.

Gelman, A., 2006. Multilevel (hierarchical) modeling: what it can and can’t do. *Technometrics*, 48 (3): 432-435.

Gentry, A.H., and Lopez-Parodi, J., 1980. Deforestation and Increased Flooding of the Upper Amazon. *Science*, 210 (4476): 1354–1356.

Ghosh, M., and Rao, J.N.K., 1994. Small Area Estimation: An Appraisal. *Statistical Science*, 9 (1): 55-76

Gibson, J., and Rozelle, S., 2003. Poverty and Access to Roads in Papua New Guinea. *Economic Development and Cultural Change*; 52 (1): 159-185.

Gittell, R.J., and Vidal, A., 1998. *Community Organizing: Building Social Capital as a Development Strategy.* SAGE publications.

Glade, T., and Crozier, M.J., 2005. A review of scale dependency in landslide hazard and risk analysis. In Glade, T., Anderson, M,. and Crozier,M., eds. *Landslide hazard and risk*. Wiley, Chichester 75-138.

Glaeser, E.L., Laibson, D., Scheinkman, J.A., and Soutter, C.L., 1999.*What is Social Capital? The Determinants of Trust and Trustworthiness*. Working Paper 7216 July 1999. National Bureau of Economic Research. Cambridge, MA. Available At: http://www.nber.org/papers/w7216

Glantz, M.H. (ed.), 2005. *Usable Science 9: El Niño Early Warning for Sustainable Development in the Pacific Rim and Islands. Report of workshop held 13–16 September 2004 in the Galapagos Islands, Ecuador*. Boulder, CO: ISSE/NCAR

Goldstein, H., 1987. *Multilevel models in educational and social research*. London, Griffin; New York, Oxford University Press.

Goldstein, H, 1998. *Multilevel Models for analysing social data, Entry for ‘Encyclopaedia of Social research Methods’*. Available at: http://www.mlwin.com/hgpersonal/multilevel-models-for-social-data.pdf

Golnaraghi, M. and Kaul, R., 1995. The Science of Policymaking: responding to ENSO, *Environment*, pp. 16-44.

Gómez, H., and Kavzoglu, T., 2005. Assessment of shallow landslide susceptibility using artificial neural networks in Jabonosa River Basin, Venezuela. *Engineering Geology*, 78, 11–27

Gray, C.L. Bremner, J.L., and Holt F.L., 2005. Multilevel determinants of indigenous land use in the Northern Ecuadorian Amazon: a cross-cultural study. *International Union for the Scientific Study of Population, XXV International Population Conference*, Tours, France, July 18-23, 2005. Available at: http://iussp2005.princeton.edu/download.aspx?submissionId=52269

Green, S. E., Rich, T. A., and Nesman, E. G., 1985. Beyond Individual Literacy : the Role of Shared Literacy for Innovation in Guatemala. *Human Organization,* 44: 313-21.

Griffiths, P., Madise, N., Whitworth, A., and Matthews, Z., 2004. A tale of two continents: a multilevel comparison of the determinants of child nutritional status from selected African and Indian regions. *Health and Place* 10: 183–199.

Grootaert, C.,1999. *Social capital, household welfare and poverty in Indonesia*. Local Level Institutions working paper no. 6. Washington, DC, Social Development Department, World Bank.

Grootaert, C., and Narayan, D., 2004. Local Institutions, Poverty and Household Welfare in Bolivia. *World Development,* 32 (7): 1179–1198.

Grosh M.E., and Muñoz, J., 1996. *A Manual for Planning and Implementing the Living Standards Measurement Study Survey*. Living Standards Measurement Study Working Paper No. 126. Washington, D.C., World Bank.

Guzzetti. F., 2000. Landslide fatalities and the evaluation of landslide risk in Italy. *Engineering Geology,* 58: 89–107

Hadadd, L, and Maluccio, J., 2000. *Social capital and Household Welfare in South Africa: Pathways of Influence*. Centre for the Study of African Economies.

Hahn, M.B., Riederer, A.M., and Foster, S.O., 2009. The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change--A case study in Mozambique. *Global Environmental Change,* 19**:** 74.

Hall, A., 2005. Globalized Livelihoods. International Migration and Challenges for Social Policy: The Case of Ecuador. *Arusha Conference, "New Frontiers of Social Policy"* – December 12th -15th, 2005.

Hall, J.W., Sayers, P.B., and. Dawson, R.J., 2005. National-scale Assessment of Current and Future Flood Risk in England and Wales. *Natural Hazards*, 36, 147–164

Heijmans, A., 2001. *Vulnerability: A Matter of Perception*. 4/2001, Benfield Greig Hazard Research Centre, University College London, London.

Hentschel, J., Lanjouw, J. O., Lanjouw, P., and Poggi, J., 2000. Combining Census and Survey Data to Study Spatial Dimensions of Poverty: A Case Study of Ecuador. In: Bigman, D., and Fofack, H., eds. *Geographical targeting for poverty alleviation: methodology and applications*. Washington D.C.

Hentschel, J., and Lanjouw, P., 1996. *Constructing an Indicator of Consumption for the Analysis of Poverty: Principles and Illustrations with Reference to Ecuador*. Living Standards Measurement Study Working Paper No. 124. Washington D.C., World Bank.

Hentschel, J. and Waters, W.F., 2002. Rural Poverty in Ecuador: Assessing Local Realities for the Development of Anti-poverty Programs. *World Development*, 30: 33-47.

Hererra, G., 2001. Los estudios de género en el Ecuador: entre el conocimiento y el reconocimiento. In Hererra, G. ed. *Estudios de género*. Quito, FLACSO.

Hewitt, K., 1983. The idea of calamity in a technocratic age. In Hewitt, K. ed. *Interpretations of Calamity*. Winchester, MA, Allen and Unwin.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. and Jarvis, A., 2005. Very High Resolution Interpolated Climate Surfaces for Global Land Areas. *International Journal of Climatology*, 25: 1965–1978

Hill, M.S, 1992. *The Panel Study of Income Dynamics: a user's guide*. Newbury Park, California/London, England, Sage Publications, 1992. xiv, 89 p. (Guides to Major Social Science Data Bases No. 2)

Hoddinott, J., Quisumbing, A., de Janvry, A., and Woldehanna, T., 2005. *Pathways from Poverty: Evaluating Long-Term Strategies to Reduce Poverty*. BASIS CRSP Brief No. 30, Madison, University of Wisconsin, Department of Agricultural and Applied Economics. Accessible at http://www.basis.wisc.edu

Hodgson, A., Smith, T., Gagnew, S., Adjuik, M., Muschkez, G., Mensah, N.K., Binka, F and Genton, B., 2001. Risk factors for meningococcal meningitis in northern Ghana. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, 95: 477-480

Holling, C. S.,1973. Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics*, 4: 1-23.

Hong, Y., Adler, R.F., Negri, A., and Huffman, G.J., 2007. Flood and Landslide Applications of Near Real-time Satellite Rainfall Estimation, *Journal of Natural Hazards*, 43: 285–294

Horel, J.D. and Wallace, J.M., 1981. Planetary-Scale Atmospheric Phenomena Associated with the Southern Oscillation. *Monthly Weather Review*, 109: 813-829.

Hox, J.J., 1995. *Applied multilevel analysis*. Amsterdam, Netherlands, TT-Publikaties, ISBN 90-801073-2-8.

Huigen, M.G.A., and Jens, I.C, 2006. Socio-Economic Impact of Super Typhoon Harurot in San Mariano, Isabela, the Philippines. *World Development*, 34 (12): 2116 –2136,

Humphrey, J., 1994. Are the Unemployed Part of the Urban Poverty Problem in Latin America? *Journal of Latin American Studies*, 26: 713.

Instituto Nacional de Meteorología e Hidrología (INAMHI), 1998. *Fenómeno de El Niño 1997-98, Evaluación meteorológica – Informe final 1998*, Quito

Instituto Nacional de Meteorología e Hidrología (INAMHI), 1999. *Fenómeno de El Niño 1997-98, Evaluación hidrológica*, Quito, 35p. + mapa "Zonas inundadas por el fenómeno El Niño 1997-98" Escala 1:1,000,000

Instituto Nacional de Meteorología e Hidrología (INAMHI), 2005. *Estudio Hidrológico de Caudales Máximos y Levantamiento de Información Ambiental de la Cuenca del Río Zarumilla*. Quito, Ecuador, March 2005.

Instituto Nacional de Meteorología e Hidrología (INAMHI), 2007. *Información hidrológica mensual*. Available at: http://www.inamhi.gov.ec/html/inicio.htm

Instituto Nacional de Estadística y Censos (INEC), 1990. *V Censo de Población y IV de Vivienda*. Quito, Ecuador. Available at: http://redatam.inec.gov.ec/cgibin/RpWebEngine.exe/PortalAction?&MODE=MAIN&BASE=CPV1990&MAIN=WebServerMain.inl

Instituto Nacional de Estadística y Censos (INEC), 2003. *Sistema Integrado de Consultas a los Censos Nacionales*.

Instituto Nacional de Estadística y Censos (INEC), 2008. *Sistema Integrado de Indicadores Sociales del Ecuador (SIISE)*. Quito, Ecuador. Available at: http://www.siise.gov.ec/

Instituto Nacional de Estadística y Censos (INEC) and Servicio Ecuatoriano de Capacitación Profesional, 1995. *Ecuador: Encuesta de Condiciones de Vida (ECV) Bases Metodologicas, Técnicas y Procedimientos*. Grupo Técnico SECAP, February 1995, Quito, Ecuador. Available at: www.worldbank.org/LSMS/country/ecuador/docs/metodox.pdf

Instituto Nacional de Estadística y Censos (INEC) and World Bank, 1995. *Encuesta de Condiciones de Vida: Segunda Ronda*. Quito, Ecuador. Available at: http://www.worldbank.org/lsms/

Instituto Nacional de Estadística y Censos (INEC) and World Bank, 1998. *Encuesta de Condiciones de Vida: Tercera ronda*. Quito, Ecuador. Available at: http://www.worldbank.org/lsms/

International Federation of the Red Cross and Red Crescent Societies, 2009. World Disasters Report 2009.

Islam, M.D.M., and Sado, K., 2000. Development of flood hazard maps of Bangladesh using NOAA-AVHRR images with GIS. *Hydrological Sciences-Journal-des Sciences Hydrologiques*, 45 (3): 337-355

Izquierdo, S., 2004. Demography and Migration in Ecuador. *International Conference "Statisitics – investment in the future"*, Prague, Czech Republic, 6th-7th September, 2004. Available at: http://www.czso.cz/sif/conference2004.nsf/i/1766A8F2B8987A42C1256EDA00436D3C/$File/Santiago%20Izquierdo.pdf

Jacoby, H.G., 2000. Access to markets and the benefits of rural roads. *The Economic Journal*, 110 (July): 713 – 737.

Jain, M.K, Kothyari, U.C., and Ranga Raju, K.G., 2004. A GIS based distributed rainfall–runoff model. *Journal of Hydrology*, 299: 107–135

Jalan, J., and Ravallion, M., 2002. Geographic Poverty Traps? A Micro Model of Consumption Growth in Rural China. *Journal of Applied Econometrics*, 17: 329–346

Janelid, I., 1980. Rural Development Programmes and the Farm Household as a Unit of Observation and Action. In: Presvelou, C., and Spijkers-Zwart, S. I. eds. *The Household, Women and Agricultural Development*. Miscellaneous Papers 17 (1980), Wageningen, Netherlands.

de Janvry, A. and Sadoulet, E., 1996. Household Modeling for the Design of Poverty Alleviation Strategies. *European Association of Agricultural Economists VIII Congress*. Edinburgh, Scotland. Available at: http://are.berkeley.edu/~sadoulet/papers/Edimburg_text.pdf

Jarvis, A., Nelson, A., Rubiano, J., Farrow, A. and Mulligan, M., 2004. *Practical Use of SRTM data in the tropics – Comparisons with digital elevation models generated from cartographic data*. Cali, Colombia, CIAT.

Jaspars, S. and Shoham, J., 1999. Targeting the Vulnerable: A Review of the Necessity and Feasibility of Targeting Vulnerable Households. *Disasters*, 23 (4): 359-372.

Jokisch, B.D., 2002. Migration and Agricultural Change: The Case of Smallholder Agriculture in Highland Ecuador. *Human Ecology*, 30 (4): 523-550

Jokisch, B.D., and Pribilsky, J., 2002. The Panic to Leave: Economic Crisis and the “New Emigration” from Ecuador. *International Migration*, 40 (4): 75-101

Jolliffe, D., 1997. *Whose Education Matters in the Determination of Household Income: Evidence from a Developing Country*. FCND Discussion Paper No. 39, November 1997. Washington, D.C., Food Consumption and Nutrition Division, International Food Policy Research Institute.

Kamanou, G. and Morduch, J., 2002. *Measuring Vulnerability to Poverty*. UNU/WIDER.

Katz, E., 1998. *Gender and the Demographic Determinants of Migration in Ecuador*. Unpublished Paper.

Kef, S., Hox, J.J., Habekothé, H.T., 2000. Social networks of visually impaired and blind adolescents. Structure and effect on well-being. *Social Networks*, 22: 73–91

Kelly, P. M., and Adger, W. N., 2000. Theory and Practice in Assessing Vulnerability to Climate Change and Facilitating Adaptation. *Climatic Change*, 47: 325.

Krishna, A., 2000. Creating and harnessing social capital. In Dasgupta P., and Serageldin, I., eds, *Social Capital: A Multifaceted Perspective*, Washington, DC: World Bank.

Kristjanson, P., Radeny, M., Baltenweck, I., Ogutu, J., Notenbaert, A., 2005. Livelihood mapping and poverty correlates at a meso-level in Kenya. *Food Policy*, 30 (5-6): 568-583.

Kruseman, G., Hengsdijk, H., Ruben, R., Roeballing, P., and Bade, J., 1997. *Farm household modeling system for the analysis of sustainable land use and food security: Theoretical and mathematical description*. DLV_Report No. 7. Wageningen, April 1997.

Kumar, N., 2007. *Spatial Sampling for Demography and Health Survey*. Iowa City, University of Iowa. Available at: http://jh302-nk-01.iowa.uiowa.edu/papers/NK_PrPr_March_2007WithFigures.pdf

Kurosaki, T. and Khan, H., 2001. *Human Capital and Elimination of Rural Poverty: A Case Study of the North-West Frontier Province, Pakistan*. IER Discussion Paper

Series B. Hitotsubashi University. Available at: http://www.ier.hit-u.ac.jp/~kurosaki/ids1999r.pdf

Langford, I.H., and Bentham, G., 1996. Regional Variations in Mortality Rates in England and Wales: An Analysis Using Multi-Level Modelling. *Social Science and Medicine*, 42 (6): 897-908

Lanjouw, J.O., 1998. *Demystifying Poverty Lines*. New York, UNDP Poverty Elimination Programme.

Lanjouw, P., and Stern, N., 1991. 'Poverty in Palanpur'. *The World Bank Economic Review*, 5 (1)

Larrea, C., 2005. *Modelos Empleados en Mapas del Censo 2001*. Available at http://www.ecuamapalimentaria.info

Larrea, C., 2004. *Pobreza, Dolarización y Crisis en el Ecuador*. Quito, Abyayala.

Larrea, C., Andrade, J., Brborich, W., Jarrín, D., and Reed, C., 1996. *Geografía de la pobreza en el Ecuador*. PNUD-FLASCO, Quito, Ecuador.

Larrea, C., Carrasco, F., Cervantes, J., and Viedma, N., 1999. *INFOPLAN: Atlas para el desarrollo local*. Quito: ODEPLAN Presidencia de la República, Secretaría General de la Presidencia, CONAM y COSUDE, 1999

Larrea, C. and Kawachi, I., 2005. Does economic inequality affect child malnutrition? The case of Ecuador. *Social Science and Medicine*, 60: 165–178.

Larsen, M.C., and Torres-Sánchez, A.J., 1998. The frequency and distribution of recent landslides in three montane tropical regions of Puerto Rico. *Geomorphology*, 24 (4): 309-331

Leclerc, G., 2010. Scaling Up Local Perceptions of Poverty to Country Level: A Proof of Concept for Rural Honduras. *Poverty & Public Policy*, 2 (2): 103-143.

Lee, S., and Choi, J., 2004. Landslide susceptibility mapping using GIS and the weight-of-evidence model. *International Journal of Geographical Information Science*, 18 (8): 789–814

Lee, S., and Evangelista, D.G., 2005. Landslide Susceptibility Mapping using Probability and Statistics Models in Baguio City, Philippines. *31st International Symposium on Remote Sensing of Environment*, 20-24 May, 2005 Saint Petersburg. Russia. Available at: http://www.isprs.org/publications/related/ISRSE/html/papers/407.pdf

Lee, S., and Evangelista, D.G., 2006. Earthquake-induced landslide-susceptibility mapping using an artificial neural network. *Natural Hazards and Earth System Sciences*, 6: 687–695

Lehner, B. and Döll, P., 2004. Development and validation of a global database of lakes, reservoirs and wetlands. *Journal of Hydrology*, 296 (1-4): 1-22

Lehner, B., Verdin, K., Jarvis, A., 2006. *HydroSHEDS Technical Documentation*. World Wildlife Fund US, Washington, DC. Available at http://hydrosheds.cr.usgs.gov.

Liu, J.G., Mason, P.J., Clerici, N., Chen, S., Davis, A., Miao, F., Deng, H., and Liang, L., 2004. Landslide hazard assessment in the Three Gorges area of the Yangtze River using ASTER imagery: Zigui–Badong. *Geomorphology*, 61: 171–187

Lok-Dessallien, R., 2000. *Review of Poverty Concepts and Indicators*. UNDP Social Development and Poverty Elimination Division (SEPED) Series on Poverty Reduction. http://www.undp.org/poverty/publications/pov_red/Review_of_Poverty_Concepts.pdf

Lu G.Y., Chiu L.S. and Wong D.W., 2007. Vulnerability assessment of rainfall-induced debris flows in Taiwan. *Natural Hazards*, 43: 223–244

Lundberg, S., and Pollak, R.A., 1993. Separate Spheres Bargaining and the Marriage Market. *Journal of Political Economy*, 101(6): 988-1010

Ma, D., Chen, J., Zhang, W., Zheng, L. and Liu, Y., 2007. Farmers' vulnerability to flood risk. *Journal of Geographical Sciences*, 17: 269.

Maki, A., 2006. Changes in Japanese household consumption and saving behavior before, during and after the Bubble era: empirical analysis using NSFIE micro-data sets. *Japan and the World Economy*, 18: 2–21.

Maltsoglou, I., and Taniguchi, K., 2004. *Poverty, Livestock and Household Typologies in Nepal*. Roma, Food and Agriculture Organization of the United Nations.

Martins J., 2005. The impact of the use of energy sources on the Quality of Life of poor communities. *Social Indicators Research*, 72: 373–402.

Mauro, P., 1998. Corruption and the composition of government expenditure. *Journal of Public Economics*, 69: 263.

Max-Neef, M.A., 1991. *Human Scale Development: Conception, Application and Further Reflections*. New York and London, Apex Press.

Maxwell, S. and Frankenburger, T.R., 1992. *Household Food Security: Concepts, Indicators, Measurements. A Technical Review*. New York, Rome, UNICEF, IFAD.

McLaughlin, P., and Dietz, T., 2008. Structure, agency and environment: Toward an integrated perspective on vulnerability. *Global Environmental Change*, 18**,** 99.

Metzger, M. and Schröter, D., 2006. Towards a spatially explicit and quantitative vulnerability assessment of environmental change in Europe. *Regional Environmental Change*, 6: 201.

Miguel, E., and Gugerty, M.K., 2005. Ethnic diversity, social sanctions, and public goods in Kenya, *Journal of Public Economics*, 89: 2325–2368

Ministerio de Agricultura y Ganadería, 1974. *Mapa de Suelos, Cantón Macará, Provincia de Loja, escala 1:25,000*. Quito, Ecuador, Ministerio de Agricultura y Ganadería, Dirección de Planificación, Departamento de Regionalización, Sección Edafología, November 1974.

Ministerio de Salud Pública (MSP), 1999. *Fenómeno de El Niño : Memoria 1997-1998*. Quito, Ecuador, Ministerio de Salud Pública. Available at: http://cidbimena.desastres.hn/docum/crid/CD_nino/pdf/spa/doc11110/doc11110.htm

Minot, N., and, Baulch, B., 2005. Spatial patterns of poverty in Vietnam and their implications for policy. *Food Policy*, 30: 461.

Mitchell, K.M., 2003. *Citizen Surveys and Focus Groups: An Evaluation of Two Citizen Involvement Techniques in Natural Hazard Mitigation Planning*. Department of Planning, Public Policy and Management. University of Oregon.

Moore, S., Daniel, M., Linnan, L., Campbell, M., Benedict, S. and Meier, A., 2004. After Hurricane Floyd Passed. *Family and Community Health*, 27: 204.

McPeak, J., 2004. Contrasting income shocks with asset shocks: livestock sales in northern Kenya. *Oxford Economic Papers*, 56: 263-284.

Moser, C., 1998. The Asset Vulnerability Framework: Reassessing Urban Poverty Reduction Strategies. *World Development*, 26(1): 1-19.

Moser, C., 2008. Assets and Livelihoods: A Framework for Asset-Based Social Policy. In Moser, C. and Dani, A.A. (Eds.) *Assets, livelihoods, and social policy.* Washington, D.C., The World Bank.

Moy, C. M., Seltzer, G. O., Rodbell, D. T. and Anderson, D. M., 2002. Variability of El Nino/Southern Oscillation activity at millennial timescales during the Holocene epoch. *Nature*, 420: 162.

Murphy, L., Bilsborrow, R., and Pichón, F., 1997. Poverty and prosperity among migrant settlers in the Amazon rainforest frontier of Ecuador. *The Journal of Development Studies*, 34, (2): 35-65

Narayan, D., Pritchett, L., 1999. Cents and sociability: Household income and social capital in rural Tanzania. *Economic Development and Cultural Change*, 47 (4): 871-897

Nathoo, T., and Shoveller, J., 2003. Do healthy food baskets assess food security? *Chronic diseases in Canada*, 24, (2-3). Available at: http://www.phac-aspc.gc.ca/publicat/cdic-mcc/24-2/c_e.html

National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA), 2008. http://trmm.gsfc.nasa.gov/

Nelson, A. and Chomitz, K.M., 2007. The Forest–Hydrology–Poverty Nexus in Central America: An Heuristic Analysis. *Environment, Development and Sustainability*, 9 (4):369-385.

Neuhäuser, B., and Terhorst, B., 2007. Landslide susceptibility assessment using “weights-of-evidence” applied to a study area at the Jurassic escarpment (SW-Germany). *Geomorphology,* 86: 12–24.

del Ninno, C., Dorosh, P. A., Smith, L. C. and Roy, D. K., 2001. *The 1998 floods in Bangladesh: disaster impacts, household coping strategies, and responses*. Washington, DC, International Food Policy Research Institute (IFPRI).

Nussbaum, M.C., 2001. Symposium on Amartya Sen’s Philosophy: 5 Adaptive preferences and women’s options, *Economics and Philosophy*, 17: 67–88.

Nyhus E.K. and Pons E., 2004. The effects of personality on earnings. *Journal of Economic Psychology*, 26: 363–384

Oak Ridge National Laboratory, 1998. *LandScan Global Population 1998 Database*. Online documentation available at: http://www.ornl.gov/sci/landscan/landscanCommon/landscan_doc-main.html

Oak Ridge National Laboratory, 2002. *LandScan™ Global Population Database*. Oak Ridge, TN: Oak Ridge National Laboratory. Available at http://www.ornl.gov/landscan/.

ODEPLAN - FAO, 2001. *Perfil Nutricional del Ecuador: Lineamientos de Política sobre Seguridad Alimentaria y Nutrición*. Quito, Ecuador, Oficina de Planificación de la Presidencia de la República, ODEPLAN, Food and Agriculture Organisation of the United Nations, FAO.

OED Online, 2010. Oxford University Press. Accessed 23rd July, 2010. http://dictionary.oed.com

Olson, R., Sarmiento Prieto, J. P., Olson, R., Estrada, A. and Gawronski, V., 2000. *The Marginalization of Disaster Response Institutions: The 1997-1998 El Niño Experience in Peru, Bolivia, and Ecuador*. Natural Hazards Center Special Publication. Boulder, University of Colorado.

Openshaw, S., 1983. *The modifiable areal unit problem*. Vol. 38, Concepts and Techniques in Modern Geography. Norwich , UK : Geo Books

Organisation of American States (OAS), 1991. *Plan Integral de Desarrollo de los Recursos Hídricos de la Provincia de Manabí*. Washington, D.C., Organisation of American States.

Pan, W.K.Y., Bilsborrow, R.E., 2005. The use of a multilevel statistical model to analyze factors influencing land use: a study of the Ecuadorian Amazon. *Global and Planetary Change*, 47: 232– 252.

Patt, A. G., Schröter, D., de la Vega-Leinert, A. C. and Klein, R. J. T., 2009. Vulnerability research and assessment to support adaptation and mitigation: common themes from the diversity of approaches. In Patt, A. G., Schröter, D., Klein, R. J. T. and de la Vega-Leinert, A. C. (Eds.) *Assessing Vulnerability to Global Environmental Change: Making Research Useful for Adaptation Decision Making and Policy*. London, UK, Earthscan.

Pelling, M., 2003. Toward a Political Ecology of Urban Environmental Risk: The Case of Guyana. In Zimmerer, K.S., and Bassett, T.J., eds. *Political ecology: an integrative approach to geography and environment-development studies*. New York, The Guilford Press.

Pelling, M., 2003. Social Vulnerability in the City. In Pelling, M. ed. *The Vulnerability of Cities: Natural Disasters and Social Resilience*. Earthscan.

Perreault, T., 2005. Why Chacras (Swidden Gardens) Persist: Agrobiodiversity, Food Security, and Cultural Identity in the Ecuadorian Amazon. *Human Organization*, 64, (4): 327-339

Pfefferbaum, B., Houston, J.B., Wyche, K.F., Van Horn, R.L., Reyes, G., Jeon-Slaughter, H. and North, C.S., 2008. Children Displaced by Hurricane Katrina: A Focus Group Study. *Journal of Loss and Trauma*, 13: 303 - 318.

Pimentel, D., and Kounang, N., 1998. Ecology of Soil Erosion in Ecosystems. *Ecosystems*, 1: 416–426

Polsky, C., Neff, R. and Yarnal, B., 2007. Building comparable global change vulnerability assessments: The vulnerability scoping diagram. *Global Environmental Change,* 17**:** 472-485.

Prandini, L., Guidiini, G., Bottura, J.A., Pançano, W.L. and Santos, A.R., 1977. Behavior of the vegetation in slope stability: A critical review. *Bulletin of Engineering Geology and the Environment*, 16 (1): 51-55

Putnam, R.D., 1995. Bowling Alone: America’s Declining Social Capital. *Journal of Democracy*, 6 (1): 65-78

Rakodi, C.,1999. A Capital Assets Framework for Analysing Household Livelihood Strategies: Implications for Policy. *Development Policy Review*, 17: 315-342.

Rasbash, J., Browne, W., Goldstein, H., Yang, M., Plewis, I., Healy, M., Woodhouse, G., Draper, D., Langford, I., and Lewis, T., 2002. *A User’s guide to MLwiN*. London, Centre for Multilevel Modelling, Institute of Education, University of London.

Rasmusson, E.M. and Wallace, J.M., 1983. Meteorological Aspects of the El Nino/Southern Oscillation. *Science*, 222: 1195-1202.

Ravnborg, H.M., 1999. *Developing regional poverty profiles based on local perceptions*. Cali, Colombia, International Center for Tropical Agriculture (CIAT).

Restrepo, H.E., 2001. *Technical Report: increasing community Capacity and Empowering Communities for Promoting Health*. Available at: http://www.who.int/hpr/conference/products/Techreports/community.pdf

Reuter, H.I., Nelson, A. and Jarvis, A., 2007. An evaluation of void-filling interpolation methods for SRTM data. *International Journal of Geographical Information Science*, 21 (9): 983 - 1008

Robinson, W. S., 1950. Ecological correlations and the behavior of individuals. *American Sociological Review*, 15: 351–57

Rodda, H.J.E., 2005. The Development and Application of a Flood Risk Model for the Czech Republic. *Natural Hazards*, 36: 207–220

Rossel, F., le Goulven, P., and Cadier, E, 1999. Répartition spatiale de l'influence de l'ENSO sur les précipitations annuelles en Equateur. *Revue des sciences de l'eau* (Paris), 12 (1):183-200.

Rudel, T.K., 2000. Organizing for Sustainable Development: Conservation Organizations and the Struggle to Protect Tropical Rain Forests in Esmeraldas, Ecuador. *Ambio*, 29 (2): 78-82.

Ryan, G.W. and Bernard, H.R., 2003. Techniques to Identify Themes. *Field Methods*, 15: 85-109.

Ryan, G.W. and Bernard, H.R., 2000. Data management and analysis methods. In Denzin, N., and Lincoln, Y., eds. *Handbook of qualitative research. 2nd ed*. Thousand Oaks, CA, Sage Publications.

Sales Jr, R. F. M., 2009. Vulnerability and adaptation of coastal communities to climate variability and sea-level rise: Their implications for integrated coastal management in Cavite City, Philippines. *Ocean and Coastal Management*, 52: 395.

Sanginga, P.C., Kamugisha, R., Martin,A. Kakuru, A., and Stroud, A., 2004. Facilitating participatory processes for policy change in natural resource management: Lessons from the highlands of southwestern Uganda. *Uganda Journal of Agricultural Sciences*, 9: 958-970.

Santos, M. E., Lugo, M. A., Lopez-Calva, L. F., Cruces, G. and Battiston, D., 2010. Refining the Basic Needs Approach: A Multidimensional Analysis of Poverty in Latin America. *Research on Economic Inequality*, 18**:** 1-29.

Sartore, G., Kelly, B., Stain, H., Albrecht, G. and Higginbotham, N., 2008. Control, uncertainty, and expectations for the future: a qualitative study of the impact of drought on a rural Australian community. *Rural and Remote Health*, 8: 950.

Schröter, D., Polsky, C., and Patt, A., 2005. Assessing vulnerabilities to the effects of global change: an eight step approach. *Mitigation and Adaptation Strategies for Global Change*, 10 (4): 573–595.

Scoones, I., 1998. *Sustainable Rural Livelihoods: a framework for analysis*. Brighton, IDS.

Sen, A.K., 1999. *Development as Freedom*. Oxford, Oxford University Press.

Sen, A.K., 1987. *Gender and Cooperative Conflicts*. WIDER Working Papers. Oxford, United Nations University.

Sen, A.K., 1981. *Poverty and Famines: an essay on entitlement and deprivation*. Oxford, Oxford University Press, 288 pp.

Siepel, A.C., Steenhuis, T.S., Rose, C.W., Parlange, J.Y and McIsaac, G.F., 2002. A simplified hillslope erosion model with vegetation elements for practical applications. *Journal of Hydrology*, 258 (1-4): 111-121

Sierra, R., Campos, F., and Chamberlin, J., 2002. Assessing biodiversity conservation priorities: ecosystem risk and representativeness in continental Ecuador. *Landscape and Urban Planning*, 59 (2): 95-110

Simpson, J., Kummerow, C., Tao, W.K., and Adler, R.F., 1996. On the Tropical Rainfall Measuring Mission (TRMM). *Meteorology and Atmospheric Physics*, 60: 19-36

Skoufias, E., 2003. Economic Crises and Natural Disasters: Coping Strategies and Policy Implications. *World Development*, 31(7): 1087–1102

Smith, K., 2001. *Environmental Hazards. Assessing Risk and Reducing Disaster*, 3rd ed. London –New York, Routledge.

Smith, S. and McCarty, C., 1996. Demographic Effects of Natural Disasters: A Case Study of Hurricane Andrew. *Demography*, 33: 265-275.

Solberg, S., Hale, D. and Benavides, J., 2003. *Natural Disaster Management and the Road Network in Ecuador: Policy Issues and Recommendations*. Washington, D. C., Sustainable Development Department: Inter-American Development Bank.

Souris M., 2001. *República del Ecuador: modelo numérico del relieve, escala 1:1000000*. Numeric model calculated from topographic map sheets of the IGM (1:50000, 1:100000), edited and distributed by Instituto Geográfico Militar, Quito

Soussan, J., Blaikie, P., Springate-Baginski, O. and Chadwick, M., 2001. *Understanding Livelihood Processes and Dynamics. Livelihood-Policy Relationship in South Asia*, Working Paper 1, University of Leeds, UK. Available at: http://www.york.ac.uk/inst/sei/prp/pdfdocs/1_livelihoods.pdf

SPSS for Windows, Rel. 12.0.0., 2003. Chicago: SPSS Inc.

Sretzer, S. and Woolcock, M.,2002. *Health by Association? Social Capital, Social Theory and the Political Economy of Public Health*. von Hügel Institute, 3-12-2002.

Stephenson, S., 2001. Street Children in Moscow: using and creating social capital. *The Sociological Review*, 2001, 530-547.

Stillwell H. D, 1992. Natural Hazards and Disasters in Latin America. *Natural Hazards*, 6: 131-159.

Streeton, P. 1981. *First Things First: Meeting Basic Human Needs in Developing Countries*. New York: Oxford University Press.

Swift, J., 1989. Why Are Rural People Vulnerable to Famine? In Chambers, R. ed. *IDS Bulletin 20 (2): Vulnerability: How the Poor Cope*. Institute of Development Studies.

Tapsell, S.M., Penning-Rowsell, E.C., Tunstall, S.M. and Wilson, T.L., 2002. Vulnerability to flooding: health and social dimensions. *Philosophical Transactions: Mathematical, Physical and Engineering Sciences*, 360: 1511-1525.

Taylor, M.F., Brice J., Buck N., and Prentice-Lane E., 2007. *British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices*. Colchester: University of Essex. ISBN 978 1 85871 147 8

Teşliuc, E., and Lindert, K., 2001. *Guatemala Poverty Assessment Program, Vulnerability and Safety Nets: A Quantitative and Qualitative Assessment, Approach and Concept Paper (draft)*, (mimeo). Washington DC,: The World Bank, September 2001.

Tesliuc, E.D. and Lindert, K., 2002. Vulnerability: A Quantitative and Qualitative Assessment. *IFPRI-World Bank Conference on Risk and Vulnerability: Estimation and Policy Implications*, Washington, D.C., USA, pp. 91.

Tesliuc, E., and Lindert, K., 2003. The Impact of Vulnerability and Shocks on the Poor: The Guapa Program in Guatemala. *En Breve 22*. Washington, D.C., World Bank.

Thomas, T.S., 2003. A Macro-Level Methodology for Measuring Vulnerability to Poverty, with a Focus on MENA Countries. *Fourth Annual Global Development Conference Globalization and Equity*. Cairo, Egypt, January 21st, 2003

Tibaldi A., Ferrari L., and Pasquare G., 1995. Landslides triggered by earthquakes and their relations with faults and mountain slope geometry: an example from Ecuador. *Geomorphology*, 11 (3): 215-226

de la Torre, García-Saltos, R, and Mascaró, Y., 2001. *Banking, Currency, and Debt Meltdown: Ecuador Crisis in the Late 1990s (draft)*, October 2001. The World Bank, Washington D.C. Available at:
http://wbln0018.worldbank.org/lac/lacinfoclient.nsf/fa27230f25db1df885256950004f

7138/acf36c603108ca8f85256c220073143a/$FILE/Ecuador-%20Financial%20Crisis%20compiled.pdf

Toth, E., Brath, A., and Montanari, A., 2000. Comparison of short-term rainfall prediction models for real-time flood forecasting. *Journal of Hydrology*, 239: 132–147

Tran, P., Marincioni, F., Shaw, R., Sarti, M. and Van An, L., 2008. Flood risk management in Central Viet Nam: challenges and potentials. *Natural Hazards*, 46**,** 119-138.

Twigg, J., 2001. *Sustainable Livelihoods and Vulnerability to Disasters*. Disaster Management Working Paper, 2/2001. Benfield Greig Hazard Research Centre, University College London, London.

Twigg, J., 2007. *Tools for Mainstreaming Disaster Risk Reduction: Sustainable Livelihoods Approaches*. Geneva, Switzerland, ProVention Consortium.

Ulimwengu, J.M., and Kraybill, D.S., 2004. Poverty over Time and Location: an Examination of Metro-Nonmetro Differences. *American Journal of Agricultural Economics*, 86 (5): 1282-1288

United Nations Development Program (UNDP), 1990. *Human Development Report*

United States Geological Survey (USGS), 2000. *HYDRO1k Elevation Derivative Database*. USGS EROS Data Center, Sioux Falls, SD. Available at http://edc.usgs.gov/products/elevation/gtopo30/hydro/

United States Geological Survey (USGS), 2006. *Shuttle Radar Topography Mission DTEDH Level 1 (3-arc second) documentation*. Available online at: http://edc.usgs.gov/products/elevation/srtmdted.html

United States Soil Conservation Service, 1986.*Technical Release 55: Urban Hydrology for Small Watersheds*. United States Department of Agriculture (USDA).

June 1986. Available at:
ftp://ftp.wcc.nrcs.usda.gov/downloads/hydrology_hydraulics/tr55/tr55.pdf .

Uquillas, J.E., and van Nieuwkoop, M., 2003. *Social Capital as a Factor in Indigenous Peoples Development in Ecuador*. Sustainable Development Working Paper 15, August 2003, Indigenous Peoples Development Series, Latin America and Caribbean Region, The World Bank, Washington D.C. Available at:
http://lnweb18.worldbank.org/ESSD/sdvext.nsf/60ByDocName/SocialCapitalasaFactorinIndigenousPeoplesDevelopmentinEcuadorLatinAmericaandCaribbeanRegionSustainableDevelopmentWorkingPaper15/$FILE/Social+Capital+and+Indigenous+Development.pdf

Vargas, R., Molina, M., Bayarri, S. and Campos, A., 2009. *The Andean Information System for Disaster Prevention and Relief: SIAPAD an initiative for the development of a thematic SDI*. GSDI 10. Trinidad.

Varnes, D.J., 1984. *Landslide hazard zonation: a review of principles and practice*. ISBN 92-3-101895-7, UNESCO, Paris, France pp63.

Vásquez, N., 2005. Gestión Integral del Riesgo por Inundaciones: Caso de Estudio Ciudad de Chone. *XXXIII Curso Internacional de Geografía Aplicada: Geografía y Riesgos Ambientales*. Quito, Centro Panamericano de Estudios e Investigaciones Geográficas (CEPEIGE).

Vatsa, K.S., 2004. Risk, Vulnerability, and Asset-based Approach to Disaster Risk Management. *International Journal of Sociology and Social Policy*, 24: 1-48.

van der Veen, A. and Logtmeijer, C., 2005. Economic Hotspots: Visualizing Vulnerability to Flooding. *Natural Hazards*, 36: 65.

Villa, F., and McLeod, H., 2002. Environmental Vulnerability Indicators for Environmental Planning and Decision-Making: Guidelines and Applications. *Environmental Management*, 29: 335.

Vos, R., and De Jong, N., 2000. *Rising Inequality during Economic Liberalisation and Crisis: Macro or Micro Causes in Ecuador's Case?* Working Paper 326, Institute of Social Studies, The Hague, The Netherlands, ISSN 0921-0210.

Vos, R., Velasco, M. and de Labiastida, E., 1999. *Economic and Social Effects of "El Niño" in Ecuador.* Working Paper 292, Institute of Social Studies, The Hague, The Netherlands.

Vuille, M., Bradley, R. S. and Keimig, F., 2000. Climate Variability in the Andes of Ecuador and Its Relation to Tropical Pacific and Atlantic Sea Surface Temperature Anomalies. *Journal of Climate*, 13: 2520-2535.

Wagner, H.,2004. Migrantes Ecuatorianas en Madrid: Reconstruyendo Identidades de Género. *Ecuador Debate*, 63.

Van Walsum, P.E.V., Veldhuizen, A.A., Van Bakel, P.J.T., Van Der Bolt, F.J.E., Dik, P.E., Groenendijk, P., Querner, E.P. and Smit, M.F.R., 2005. *SIMGRO 5.0.1, Theory and model implementation*. Alterra ,Wageningen, Netherlands.

Wang, H. B., and Sassa, K., 2005. Rainfall-induced landslide hazard assessment using artificial neural networks. *Earth Surface Processes and Landforms*, 31: 235–247.

Wang, S., 2005. Characteristics of Large Low-frequency Debris Flow Hazards and Mitigation Strategies, *Journal of Mountain Science*, 2 (1): 50-58

Webb, P. and Harinarayan, A, 1999. A Measure of Uncertainty: The Nature of Vulnerability and Its Relation to Malnutrition. *Disasters*, 23(4): 292-305.

Wilhelmi, O. V. and Wilhite, D. A., 2002. Assessing Vulnerability to Agricultural Drought: A Nebraska Case Study. *Natural Hazards*, 25: 37.

Winograd, M., 2007. Sustainability and vulnerability indicators for decision making: lessons learned from Honduras. *International Journal of Sustainable Development,* 10 (1-2), 93-105.

Winograd, M., Schillinger, S., Farrow, A., and Hernandez, I., 2000. *Vulnerabilidad frente a desastres naturales en Honduras*. Cali, Colombia, International Center for Tropical Agriculture CIAT. Available at: http://gisweb.ciat.cgiar.org/Vulnerabilidad/index.htm

Wischmeier, W.H., and Smith, D.D., 1978. *Predicting Rainfall erosion Loss.* USDA. Agricultural research Service Handbook 537.

Wisner, B., 1998. Marginality and vulnerability: Why the homeless of Tokyo don't ‘count’ in disaster preparations. *Applied Geography,* 18**:** 25.

Woolcock, M., 2001. The Place of Social Capital in Understanding Social and Economic Outcomes. In J.F. Helliwell, ed. *The Contribution of Human and Social Capital to Sustained Economic Growth and Well-Being*. International Symposium Report. Human Resources Development Canada and Organisation for Economic Co-operation and Development, Hull, Quebec, pp. 65-88

World Bank, 2007. *World Development Indicators*. Available from: http://devdata.worldbank.org/dataonline/

World Bank, 2004. *Ecuador Poverty Assessment*. Report No. 27061-EC, April 2004, Poverty Reduction and Economic Management Sector Unit, Latin America and the Caribbean Region, Washington D.C.

World Bank, 1996. *Ecuador Poverty Report*. World Bank, Washington D.C., 334 pp.

Yamano, T. and Jayne, T. S., 2004. Measuring the Impacts of Working-Age Adult Mortality on Small-Scale Farm Households in Kenya. *World Development*, 32: 91.

Yusuf, A.A., and Francisco, H.A., 2009. *Climate Change Vulnerability Mapping for Southeast Asia.* January, 2009, Singapore, Economy and Environment Program for Southeast Asia (EEPSEA). Available at: http://www.idrc.ca/uploads/user-S/12324196651Mapping_Report.pdf

Zaitchik, B.F., van Es, H.M., and. Sullivan, P.J., 2003. Modeling Slope Stability in Honduras: Parameter Sensitivity and Scale of Aggregation. *Soil Science Society of America Journal*. 67: 268–278

Zevallos, O., 2002. *Proyecto Gestión del Riesgo ENSO en América Latina: Investigación Comparativa, Información y Capacitación desde una Perspectiva Social.* Informe de Avance del Segundo Año. Portoviejo, Ecuador. 5.