Spatially explicit integrated modeling and economic valuation of climate driven land use change and its indirect effects

Ian Bateman[1], Matthew Agarwala[1,2], Amy Binner[1], Emma Coombes[3], Brett Day[1], Silvia Ferrini[1,4], Carlo Fezzi[1], Michael Hutchins[5], Andrew Lovett[6], Paulette Posen[7].

Abstract

We present an integrated model of the direct consequences of climate change on land use, and the indirect effects of induced land use change upon the natural environment. The model predicts climate-driven shifts in the profitability of alternative uses of agricultural land. Both the direct impact of climate change and the induced shift in land use patterns will cause secondary effects on the water environment, for which agriculture is the major source of diffuse pollution. We model the impact of changes in such pollution on riverine ecosystems showing that these will be spatially heterogeneous. Moreover, we consider further knock-on effects upon the recreational benefits derived from water environments, which we assess using revealed preference methods. This analysis permits a multi-layered examination of the economic consequences of climate change, assessing the sequence of impacts from climate change through farm gross margins, land use, water quality and recreation, both at the individual and catchment scale.

Keywords: Integrated models; land use; agriculture; climate change; water quality; recreation; economics; spatial analysis.

---

[1] The Land, Environment, Economics and Policy Institute (LEEP), College of Social Sciences & International Studies, University of Exeter, Exeter, EX4 4QJ, UK. Contact i.bateman@exeter.ac.uk. Ian Bateman is also Adjunct Professor at: the Department of Agricultural and Resource Economics at the University of Western Australia, Perth; the Department of Economics, Waikato University; and AERU, Lincoln University, New Zealand.

[2] Department of Geography and Environment and Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, UK.

[3] School of Medicine, University of East Anglia, Norwich, NR4 7TJ, UK.

[4] Department of Economics, University of Siena, Piazza S.Francesco, 7 - 53100 Siena, Italy.

[5] Centre for Ecology and Hydrology, Crowmarsh Gifford, Wallingford, OX10 8BB, UK.

[6] School of Environmental Sciences, University of East Anglia, Norwich, NR4 7TJ, UK.

[7] Centre for Environment, Fisheries and Aquaculture Science, Pakefield Road, Lowestoft, Suffolk, NR33 0HT, UK.

1. Introduction

The ecosystem services paradigm (de Groot, et al. 2002; Boyd and Banzhaf, 2007; Wallace, 2007; Fisher et al., 2008; Fisher and Turner, 2008) underpins a rapidly improving and expanding body of research linking environmental change to human welfare (e.g. Goldstein et al 2012; Jackson et al., 2013; Lawler et al., 2014; Guerry et al., 2015). An important and promising avenue of work examines the direct impacts of changes, considering multiple ecosystem services (e.g. Nelson et al., 2009; Rockström et al., 2009) and at varying spatial scales (van Delden et al., 2011). However, even when multiple ecosystem services are considered, relatively few studies manage to capture the knock-on effects arising along a chain of interconnected ecosystem processes (Milne et al., 2009; Bennett et al., 2009). Inherent complexity and myriad interdependencies within the natural world mean that any change, whether driven by environmental processes or human behavior, is likely to have a 'domino' effect, acting upon a long chain of ecosystem services. For instance, considering livestock production in the Central French Alps, Lamarque et al., (2014) show that the direct impact of climate change on plant functional traits (see de Bello et al., 2010) drives a secondary, indirect impact upon agricultural land management, with implications for ecosystem service provision. Focusing on the United Kingdom (UK), Fezzi et al., (2015) go further by examining the direct consequences of climate change on land use and farm incomes, and the subsequent, indirect effects on fresh water quality providing a cost-effectiveness analysis of climate change adaptation strategies. Other studies link predictions of future environmental change with cost-effectiveness analyses of alternative mitigation measures (e.g. Whitehead et al 2013), but studies which complete the chain of effects in a cost-benefit framework are rare. This poses challenges for investment and policy decisions, since options that maximize net benefits cannot be robustly identified when the full range of impacts is unknown.

This paper contributes towards filling this research gap by using a spatially explicit, integrated modeling approach to examine a chain of related impacts arising from a simple climate change scenario applied to a selected river catchment and, crucially, valuing these impacts in economic terms. Using the UK's River Aire as a case study, we first examine the direct effect of climate change on agricultural land use, as mediated through changes in farming behavior. Resulting land use change (LUC) has repercussions on freshwater quality, as crop selection and livestock intensities impact nutrient run-off into rivers. Finally, we examine how changes in water quality will impact upon outdoor recreation. The integrated analysis elicits economic values throughout the chain of impacts, reporting recreation values at both the individual and catchment level (where our spatially explicit approach delivers a further contribution by revealing the key role which location plays when aggregating from individual to catchment level benefits). Including these secondary (often non-market) impacts is especially important in environmental management as their value can outweigh that of direct impacts, possibly by a large margin (Bateman et al., 2014). Furthermore, the spatially explicit nature of our analysis provides decision makers with the information necessary to permit locational targeting of interventions, enhancing the efficiency of policies to mitigate climate change effects or improve distributional equity.

This paper is organized as follows. The next section introduces the spatially sensitive agricultural land use model that underpins our initial analysis. Section 3 uses this model to examine the likely impact of a stylized climate change scenario (a uniform temperature increase by 1^{o}C throughout the country) on land use and farm incomes. Section 4 develops a spatially explicit, transferable model for predicting changes in river water quality arising from agricultural LUC within a world of altering climates. These predictions are then refined for use within the UK's River Aire catchment, for which we hold data on recreational demand and associated value. Section 5 develops a revealed preference model, encompassing the changes in the ecological quality of rivers derived previously, to predict the impact of our climate change scenario on recreational values. Section 6 presents the results of our integrated analysis, reporting recreational values at the individual and catchment scales. Section 7 concludes.

2. Land use modelling

This section briefly introduces the agricultural land use model, the data used for its estimation and provides a summary of the main results. For further details, see the supplementary materials and Fezzi and Bateman (2011).

2.1 Specification

Adapting the agricultural land use model developed by Fezzi and Bateman (2011) and expressing the farmer's objective in terms of profit maximization per unit of land, the optimal land use allocation problem can be written as:

$$\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \max_{s_1,\ldots,s_h}\{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,s_1,\ldots,s_h) : \textstyle\sum_{i=1}^{h} s_h = 1\}, \tag{1}$$

where $\pi^L(.)$ indicates profits per unit (ha) of land, **p** the vector of strictly positive output prices, **w** the vector of strictly positive input prices, L the total land available (which is kept constant for all analyses), **s** the vector of land use shares (with land allocated across h potential land uses), and **z** the vector of k other fixed factors (e.g. physical and environmental characteristics, policy incentives and constraints, etc.).

Since the profit per unit of land function is positively linearly homogenous and strictly convex in input and output prices, applying Hotelling's lemma yields output supply (y^L) and input demand (r^L) per area (hereafter referred to as input and output *intensities*) as:

$$y_i^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \frac{\partial\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L)}{\partial p_i} = \frac{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial p_i}, \text{ and} \tag{2.a}$$

$$r_j^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \frac{\partial\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L)}{\partial w_j} = \frac{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial w_j}, \tag{2.b}$$

where $\bar{s}_1, \dots, \bar{s}_h$ indicates optimal shares.

Since land is allocated optimally when shadow prices (i.e. marginal rents) are equalized across all land uses, optimal land use shares are described by:

$$\frac{\partial \pi^L(\mathbf{p}, \mathbf{w}, \mathbf{z}, L, \bar{s}_1, ..., \bar{s}_h)}{\partial s_i} = 0 \text{, for } i = 1,..., h. \tag{3}$$

When these equations are linear in the optimal land allocations (as per Fezzi and Bateman, 2011), including the constraint that the sum of shares must equal unity leads to a linear system of h equations in h unknowns, which can be solved to obtain the optimal land allocation as a function of **p**, **w**, **z** and L (see *ibid.*).

We specify the empirical profit function per hectare as a Normalized Quadratic (NQ) function. Defining w_n as the numeraire good, indicating with $\mathbf{x} = (\mathbf{p}/w_n, \mathbf{w}/w_n)$ the vector of normalized input and output (netput) prices and with $\mathbf{z}^* = (\mathbf{z}, L)$ the vector of fixed factors including policy and environmental drivers and also the total land available L, the NQ profit function can be written as:

$$\bar{\pi}^L = \alpha_0 + \sum_{i=1}^{m+n-1} \alpha_i x_i + \frac{1}{2}\sum_{i=1}^{m+n-1}\sum_{j=1}^{m+n-1} \alpha_{ij} x_i x_j + \sum_{i=1}^{h-1} \beta_i s_i + \frac{1}{2}\sum_{i=1}^{h-1}\sum_{j=1}^{h-1} \beta_{ij} s_i s_j + \sum_{i=1}^{k+1} \gamma_i z_i^* + \\ + \frac{1}{2}\sum_{i=1}^{k+1}\sum_{j=1}^{k+1} \gamma_{ij} z_i^* z_j^* + \sum_{i=1}^{m+n-1}\sum_{j=1}^{h-1} \delta_{ij} x_i s_j + \sum_{i=1}^{m+n-1}\sum_{j=1}^{k+1} \phi_{ij} x_i z_j^* + \sum_{i=1}^{h-1}\sum_{j=1}^{k+1} \varphi_{ij} s_i z_j^*, \tag{4}$$

where $\bar{\pi}^L = \pi / w_n$ is the normalized profit per unit of land. This profit function is linearly homogeneous by construction, and symmetry can be ensured by imposing $\alpha_{ij} = \alpha_{ji}$, $\beta_{ij} = \beta_{ji}$ and $\gamma_{ij} = \gamma_{ji}$. Only h–1 land use shares appear in the profit function as the residual can be computed by difference and is therefore redundant. Input and output intensities can be derived as in (2), whereas optimal land use shares can be derived by solving the system (3) of h–1 equations with the land additivity constraint $\sum_{j=1}^{h} s_j = 1$. The resulting equations are linear functions of output prices, input prices, and fixed factors.

2.2. Data and descriptive statistics

In order to model the financial, policy and environmental drivers of LUC, we develop a unique database of land use drivers. Integrating multiple sources of information dating back to the late 1960s we identify six land use types (cereals, oilseed rape, root crops, temporary grassland, permanent grassland and rough grazing) which together cover 88% of UK agricultural land. The remaining 12% is included as a combined ‘other’ category. Summary information regarding the land use data is provided in the supplementary materials. Further data were extracted for each 2km Ordnance Survey National Grid square. Data on average annual rainfall, autumn machinery working days, mean potential evapotranspiration, median duration of field capacity, total number of degree days in the growing season and mean elevation were taken from the National Soil Resources Institute LandIS database. We also include the share of agricultural land with slope greater than 6 degrees derived via Geographic Information System (GIS) analysis of the Ordnance Survey Digital Terrain Model (DTM). The model also includes policy determinants, such as the share of each grid square designated as National Park, Nitrate Vulnerable Zone (NVZ) and Environmentally Sensitive Area (ESA). Further spatial control variables such as the distance to the closest sugar beet factory (to capture transportation costs) and the share of urban area are also included. Finally, regional output prices are included, using the agricultural output regional price statistics extracted from the UK Farm Business Survey for years 1982-2000, whereas input prices are available at the national level.

2.3 Results

Equation (4) can be estimated via maximum likelihood. Since not all farms cultivate all crops the model is specified as a multivariate Tobit (Tobin, 1958). Fezzi and Bateman (2011) illustrate a computationally-efficient Quasi Maximum Likelihood (QLM) approach which can be used when the number of Tobit equations is high, as in our case (details provided in supplementary materials). We estimate two censored Tobit systems: the 3 livestock intensity (dairy cattle, beef cattle, sheep) equation system; and the 6 land use shares (cereal, oilseed rape, root crops, temporary grassland, permanent grassland, rough grazing) system. These are the main determinants of the impact of agriculture on the environment. In fact, in a relatively small country such England, there is little variation in fertilizer inputs for a given arable crop, and therefore a single national set of surplus values for such crops is appropriate (Lord, Anthony, and Goodlass 2002). However, nutrient inputs to grassland can vary substantially depending upon the livestock intensity. Therefore, a more accurate approach is to assume that predicted changes in stocking rates indicate changes in fertilizer applications.

Table 1 reports the final parameter estimates of the land use share equations. The sign and magnitude of the coefficients are consistent with our expectations and the model fit is satisfactory. Focusing on the economic determinants, in the upper part of the table, as expected the own output price effects are always positive and the cross-price effects negative. Considering the environmental determinants of land use, reported in the lower part of Table 1, favorable conditions for crop growth (e.g. more machinery working days, flatter land, etc.) increase the share of arable land, in particular of root crops. However, effects are highly non-linear. The coefficients of the livestock equations are not reported here to preserve space, but the results are in line with those of the land use. Model results are contrasted with the established land use share model (e.g. Wu and Segerson, 1995) in Fezzi et al. (2014) and found to provide superior in and out of sample performance.

Table 1. Land use share equations parameter estimates

	Description	Cereals	Oilseed rape	Root crops	Temp. Grassland	Perm. Grassland	Rough grazing
$P_{cereals}$		0.134 ***	a	a	-0.044 **	a	a
P_{rape}		a	0.148 ****	a	a	a	a
$P_{rootcrops}$		a	a	0.027 *	a	a	a
$P_{fertilizer}$		-0.111 ***	-0.283 ****	-0.017 *	0.067 ***	-0.018	0.036 *
Set aside rate		-0.425 ****	-0.114 ***	0.003	-0.009	-0.030	-0.025 *
ESA share		-0.033 ****	-0.008 ***	0.000	0.000	0.031 ***	0.032 ***
Park share		-0.019 ***	-0.006	-0.003 ***	-0.018 ***	-0.067 ***	0.041 ***
Urban share		-0.028 **	-0.003	-0.002	0.000	0.061 ***	0.010 *
			Environmental determinants				
smore6	Slope greater than 6 degrees	-0.087 ***	-0.018 ***	0.000	-0.005	0.131 ***	0.052 ****
Coast		-0.357	-0.505 *	-0.156	1.316 ***	-0.536	1.473 ***
Alt	Altitude	14.170 ****	3.048 ***	-2.693 ****	-0.787	b	b
atl^2	-	6.333 ***	1.337 **	-0.494 **	-0.834 *	b	b
alt < 200m	-	b	b	b	b	-0.057 ****	0.004
alt > 200m	-	b	b	b	b	0.085 **	-0.156 ***
I(alt > 200m)	-	b	b	b	b	-25.55 ***	21.96 **
Mwd	Machinery working days	4.174 ****	0.079	1.619 ****	0.956 ***	-8.455 ****	-0.582
mwd^2	-	-1.283 ***	-0.416 ***	0.681 ****	0.147	-1.346 ***	0.271 **
Pt	Potential evapotranspiration	6.727 ***	1.594 *	0.331 *	-3.419 ***	-23.95 ***	12.46 ***
pt^2	-	-2.773 **	-1.919 **	0.720 **	3.401 ***	3.969 *	-7.191 ***
Fc	Field capacity	-4.794 *	-7.374 ***	-1.856 ***	0.482	7.165 *	4.394 *
fc^2	-	16.670 ***	-6.521 ***	2.896 ***	-7.498 ***	-22.22 ***	5.000 ***
Dd	Degree days in growing season	-4.228 ***	1.653 ***	-4.801 ****	4.271 ***	35.45 ****	-6.285 ***
dd^2	-	2.571 **	-0.233	1.592 ****	-1.506 **	-3.071 *	-1.179 *
Aar	Average annual rainfall	-3.726	-11.57 ****	6.056 ****	3.950 ***	-5.000	9.738 ***
aar^2	-	-1.269	-7.177 ***	1.701 ****	3.935 ***	-4.537 *	7.246 ***
Trend		0.015	0.282 ****	-0.015 ***	-0.155 ****	-0.101 ***	0.045 ***
Const	Constant	38.04 ****	-17.61 ****	6.677 ****	13.34 ****	36.18 ****	-0.884

Notes: to preserve space the residual correlations, the parameters corresponding to the variance equations, to the interactions of the environmental factors are not reported in the Table, but are available under request from the Authors. Footnotes: a = parameters non-significant and therefore removed; b = parameter not included in the equation, * = t-stat > 2, ** = t-stat > 3, *** = t-stat > 4, **** = t-stat > 10.

3. From climate change to agricultural land use change

The model estimated in the previous section can be used to predict agricultural land use in England and Wales under a variety of conditions. Clearly numerous scenarios could be considered using such a model but in the present analysis we restrict ourselves to consideration of the effects of a climate change induced increase in temperature and hold other determinants constant (an assumption that could be relaxed to examine related effects such as shifts in precipitation; see Fezzi and Bateman 2015). We first construct a baseline scenario keeping all land use determinants fixed at the level of the last year for which we have observations for the entire case study area (2004). Then we simulate the LUC arising from a simple climate change scenario obtained by holding all land use determinants (prices, policy, urbanization, etc.) constant and increasing average daily temperatures by 1^{o}C (an increase expected to occur in the UK by about 2030; UKCP, 2009). We can translate the predicted changes in land use into variations in farm income. Profit data are not available at the highly disaggregated spatial resolution used throughout our analysis. Instead we use the related and commonly adopted measure of Farm Gross Margin (FGM), defined as the difference between revenues from agricultural activities and associated variable costs. For illustrative purposes predicted changes can be reported in terms of income by simply applying the average FGM for each activity calculated from the 2004 Farm Business Survey (source: Fezzi et al., 2010) to the land use and livestock data in each 2 km^2 grid cell. Results are reported in Table 2.

Table 2. Changes in land use, livestock numbers and FGM/ha as predicted by the land use model

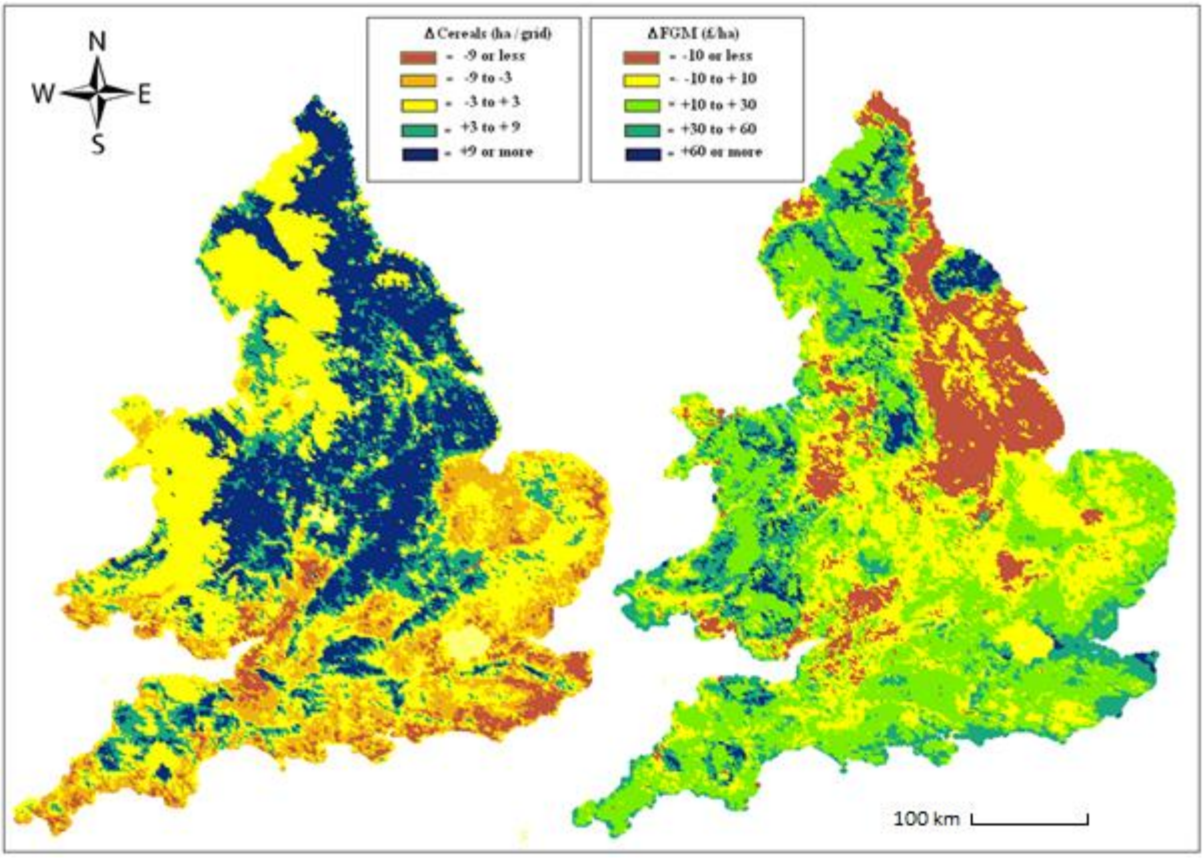
	FGM/ha (1)	Under present climate (2)	Under climate change (3)	Climate induced change in area or livestock (4)
	£/ha	**('0000 ha)**	**('0000 ha)**	**%**
Cereals	290	298.8	285.4	-4.5
Oilseed Rape	310	41.1	46.6	13.3
Root crops	2400	22.4	16.8	-25.0
T. grassland	0	78.5	83.9	6.9
P. grassland	0	415.4	697.3	67.8
Rough grazing	0	131.4	82.1	-37.5
Other	0	226.7	2.2	-99.0
	£/head	**('0000 head)**	**('0000 head)**	**%**
Dairy	570	194.5	219.6	12.9
Beef	70	462.5	506.5	9.5
Sheep	9	2194.2	2632.3	20.0

Notes: The table shows, for each land use and livestock type, the predicted impact of a 1^{o}C increase in mean daily temperature. Column (1) reports FGM values in £/ha and £/head, with predicted total agricultural land use areas and livestock heads for England and Wales (under present climate) reported in Column (2). Column (3) reports total areas and livestock numbers after the 1^{o}C temperature change, as predicted by our land use model. Column (4) reports percentage changes.

Considering arable production, the climate scenario induces a shift away from cereals and root crops towards more heat tolerant crops such as oilseed rape. There is an apparent increase in permanent grassland; however, we have some reservations about the estimated size of this effect, which may have been inflated by a decision to not directly model the 'other' land category, leaving it as a residual from which permanent grassland may have overly drawn (for a detailed discussion, see Fezzi and Bateman, 2011).

A key advantage of our modeling framework is its high spatial sensitivity. The left hand panel of Figure 1 illustrates the highly spatially heterogeneous nature of changes to the area of cereals. This area increases substantially in northern parts of the country, where warmer temperatures raise cereal yields. Conversely in the south of the country, cereal area decreases as farms substitute into other activities. As illustrated in the right hand panel of Figure 1, and in line with previous research (e.g. Fezzi et al., 2014, Fezzi and Bateman, 2015), our results confirm that climate change will generally increase farm incomes. This is in line with expectations given that the increase in temperature is likely to boost yields in the relatively cold and wet UK climate. However, some localized negative effects may be expected, mainly in the East, where higher temperatures limit high-revenue root crops.

Figure 1: Change in the spatial distribution of cereals and FGM as a result of climate change (a 1°C increase in mean daily temperature)



4. From land use change to water quality impact

Agricultural LUC alters the flow and quantity of diffuse pollution into rivers. Evaluating the impact of these changes in terms of water quality (the biological status of rivers) requires an understanding of the ecological response induced by LUC. Prior work relates land use change to spatially sensitive patterns of nutrient leaching, taking account of in-stream mixing processes to estimate the nutrient concentrations which in part determine ecological effect (Fezzi et al., 2008, 2010; Hutchins et al., 2009, 2010b). Here we directly model the relationship between land use and its ecological impact on the water environment through the commonly adopted measure of chlorophyll-*a* concentrations. This allows us to assess the overall impact of particular changes in land use rather than relying purely on nutrient models.

We use panel data observations, provided by the Centre for Ecology and Hydrology (CEH) (Davies and Neal, 2007), on the concentration of chlorophyll-*a* at individual monitoring points in rivers across England and Wales. The incidence of chlorophyll-*a*, as represented by summer mean concentration, is a measure of the rate of algal production in a water body, and is a commonly used indicator of water quality in both natural and social science research because it can both identify the risk of eutrophication of aquatic ecosystems and is directly perceived by the general public as a measure of water quality (e.g. Cullen 1982; Boyer et al. 2009).

As potential predictors of chlorophyll-*a* concentration we consider variables detailing catchment area and land use allocations, climatic and hydrological variables. Land use affects many of the physical and chemical properties of rivers, such as the quantity of suspended sediment, levels of dissolved oxygen and concentrations of nutrients such as nitrate and phosphate. Therefore, we expect land use variables to be very important in determining chlorophyll-*a* concentration and overall river ecological quality. Climatic variables considered here include temperature, solar radiation and average annual rainfall levels. Lower temperatures are expected to be associated with lower concentrations of chlorophyll-*a* as lower thermal energy inhibits algal production. Solar radiation levels are also an important contributing factor reflecting the intensity of light, which is required for algal production. Hydrological variables include suspended sediment, representing the presence of particulate matter in the water, and the base flow index, which indicates the speed and the volume of river flow. A higher base flow index typically suggests a lower residence time in the river channel environment and is generally associated with lower observed concentrations of chlorophyll-*a*, as faster flow rates inhibit algal production and dilute nutrients.

Land use and chlorophyll modeling was undertaken for river basins contributing runoff and leached nutrients at 83 Environment Agency monitoring points along river networks throughout England and Wales during 2006, thus enabling modeled data to be evaluated against observed chlorophyll concentrations. This data also includes river characteristics such as water temperature, base flow index etc. The spatial extent of each contributing river basin was derived using a digital elevation map from the Ordnance Survey Land-Form PANORAMA DTM (www.edina.ac.uk). Using data from the June Agricultural Census (www.edina.ac.uk) and MAGIC Agricultural Land Classification (www.magic.gov.uk) we derived a set of land use variables representing livestock head counts and total areas of land under various agricultural and non-agricultural uses at the basin level.

4.1 The river water quality model

The chlorophyll-*a* concentration (µg/l) model is specified as a function of land use, climatic and hydrological variables. Several functional forms were tested, beginning with a simple linear model and progressing through a variety of functional forms (including log-log, log-square and log-square root forms) allowing for non-linear and interaction effects. The best fitting model which also conforms to hydrological theory was

$$\log(\text{Chlorophyll})_{i,t} = \alpha + \boldsymbol{\beta}_{\mathbf{1}}'\boldsymbol{s}_{i,t} + \beta_2' d_{i,t} + \beta_3 \, Log(temp_{i,t}) + \beta_4 Log(BFI_{i,t}) + \beta_5 AARainfall_{i,t} + \beta_6 Log(SSediment_{i,t}) + \delta_i + e_{i,t} \quad (5)$$

where *i* denotes the monitoring point and *t* indicates whether the observation relates to summer or winter; $\boldsymbol{s}_{i,t}$ is a vector of shares of different land uses, $d_{i,t}$ is the number of dairy and beef cattle per square mile in the basin, $temp_{i,t}$ is the average atmospheric temperature, $BFI_{i,t}$ is the base flow index, $AARainfall_{i,t}$ is the annual average rainfall, $SSediment_{i,t}$indicates the quantity of suspended sediments, δ_i is a residual error term specific to the monitoring point *i* (random effect) and $e_{i,t}$ is a residual term. Both δ_i and $e_{i,t}$ are assumed to be normally distributed.

The parameters α, $\boldsymbol{\beta}_{\mathbf{1}}, \beta_2, \beta_3, \beta_4, \beta_5$ and β_6 are estimated via Generalized Least Squares (GLS) random effects model (see Green, 2002) with heteroscedasticity consistent standard errors obtained using the White (1980) correction. Results are reported in Table 3. After testing for parameter equivalence, urban and non-agricultural land shares were combined into a single category, while root crops were separated from arable land as they have a disproportionate impact on water quality due to the high levels of nutrient fertilizers used in their production. The share of rough grazing provides the baseline for comparison. The total area of the catchment was tested but consistently found to be an insignificant explanatory variable and was dropped from the model. The intensity of dairy cattle was included separately in the model as dairy farms make more intensive use of land and have higher nutrient inputs than other livestock farms whose effect on water quality is primarily captured by the grassland variables. The effect of stocking densities for other livestock, such as sheep, were examined and found to be insignificant; a finding which is echoed in studies examining other water quality measures (Crowther et al., 2011).

Table 3: Random effects (GLS) estimates of chlorophyll-*a* concentration (μg/l)

	Coefficient	**Standard Error**	**t-stat**
Constant	-3.44***	0.78	-4.41
Share of root crops	6.00*	2.82	2.13
Share of non-agricultural land	0.12	0.54	0.23
Share of other arable land	0.49	0.56	0.88
Share of temporary grassland	-3.97*	1.71	-2.32
Number of dairy cattle per square mile	0.009**	0.02	3.73
Log(Temperature)	1.97****	0.13	15.64
Annual average rainfall / 1000	-0.77*	0.29	-2.68
Log(BFI)	-0.46	0.28	-1.67
Log(Suspended sediment)	0.44***	0.096	4.56
R-squared:			
within	0.79		
between	0.70		
overall	0.73		
Number of observations	156		
Number of groups	78		

"*" = t-stat > 2, "**" = t-stat > 3, "***" = t-stat > 4, "****" = t-stat > 10.

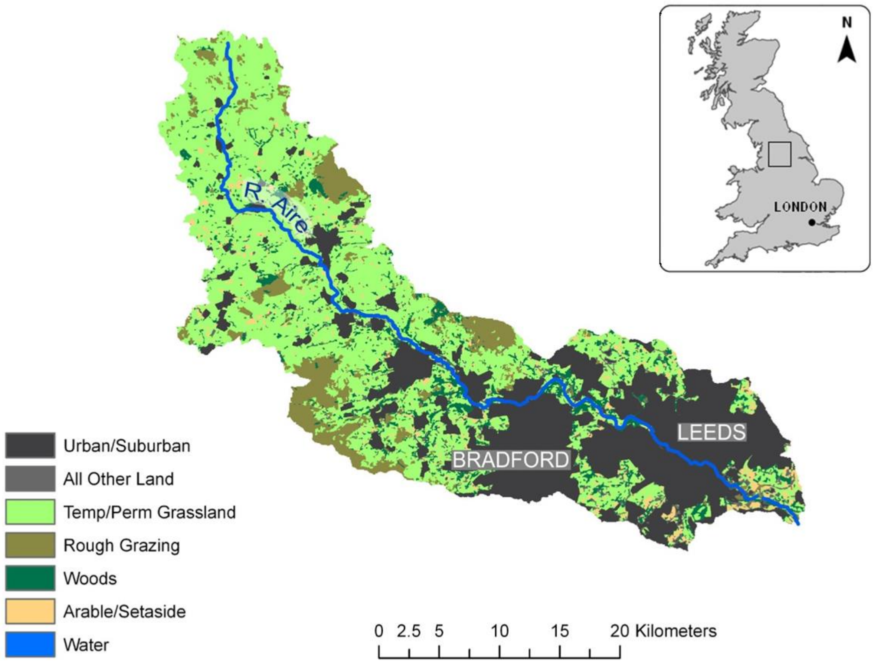
The land use share results in Table 3 are as expected. Relative to the rough grazing baseline, the share of root crops has the largest positive association with chlorophyll-*a* concentration while the share of temporary grassland has the largest negative association reflecting the fact that it is the land use which is most typically used for dairy cattle. Once we account for the intensity of dairy cattle the overall impact on chlorophyll-*a* concentration becomes even higher than that of rough grazing. Effects of the shares of non-agricultural and arable land are not statistically significant, although the signs are consistent with our expectations that a greater share of arable land is associated with a rise in chlorophyll-*a* concentrations.

The climate variables temperature and precipitation are both significant. The positive coefficient on temperature is consistent with the expectation that higher temperatures stimulate algal production, raising the concentration of chlorophyll-*a*. As temperature enters the equation in log form, its coefficient represents an elasticity. As its values is greater than one this indicates that chlorophyll concentration is elastic with respect to temperature. The negative coefficients on rainfall and the hydrological variable base flow index (the latter being just insignificant) are consistent with the expectation that a faster flowing river, in which nutrients are flushed through more quickly, leaves less time for algal growth. Conversely a positive, significant but inelastic, relationship is observed with respect to the level of suspended sediment in the river as this assists the transport of nutrients from field to waterway (Ebbert et al., 2005).

4.2 Predicting the ecological impact of climate change: A case study

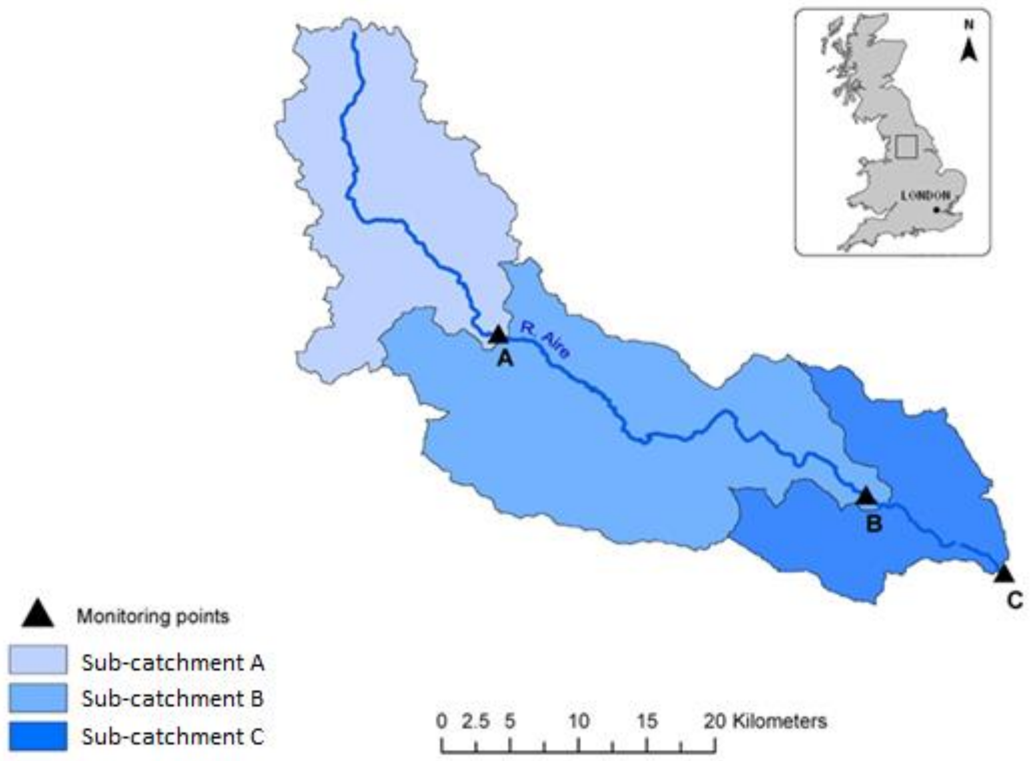
As noted, the land use and ecological quality models draw upon datasets covering large areas and are both characterized by a high level of spatial accuracy. Derived models therefore encompass a wide degree of data variability and should be generally transferable following standard out-of-sample validation tests (the methodology for which is described, for instance, in Bateman et al., 2002, 2003). As the model predictor variables are typically held for the entire coverage of the country, both land use and ecological quality estimates can be obtained for any decision-relevant area. For illustration, we consider an area for which we also hold revealed preference data for the recreational value of the freshwater environment; namely the catchment of the River Aire in Yorkshire, shown in Figure 2. This river basin covers 86,000ha and encompasses highly heterogeneous land uses, water qualities and socioeconomic characteristics. The western half of the catchment is sparsely populated, with the upland areas being dominated by rough grazing and pastoral agriculture. The remainder of the catchment includes mixed and arable farming, and some high density urban areas, including the large conurbations of Bradford and Leeds. While these urban areas are obviously unavailable for agriculture, their location is both a major determinant of river ecology and of the recreational values generated by any change in water quality.

Figure 2: Land use in the River Aire catchment



Data for the land use model are available at 2km grid resolution covering the entirety of England and Wales. In contrast data for the water quality ecological impact model are only available for an irregular network of river monitoring points administered by the UK Environment Agency (EA). The EA maintain three water quality monitoring points on the River Aire. These are used as points to transfer our ecological impact model to estimate likely changes in chlorophyll-*a* concentration, and hence water quality, arising from a 1^{o}C rise in temperature. These monitoring points allow for analysis at the catchment and sub-catchment scale, and their locations (one upstream of the urban areas, one in central Leeds and one at the catchment outlet; indicated as points A, B and C, illustrated in Figure 3) permit differentiation between the agricultural and urban impacts. The monitoring points are sited according to the physical characteristics of the catchment, taking account of hydrological response units (HRUs) corresponding to areas of land that drain into discrete river stretches (Posen et al., 2011). Aggregations of these HRUs can be thought as sub-catchments, with monitoring stations located at their outlets.

Figure 3: Three sub-catchments of the River Aire corresponding to monitoring points A, B and C.



While climate change is expected to increase the market value of agricultural production it also generates non-market costs. The induced LUC is associated with increased nutrient application, higher river pollution and lower ecological quality. This in turn generates a potentially major non-market externality in terms of impacts upon the recreational value of rivers (EPA, 2015). To estimate this value within our revealed preference analysis we need to understand the link between the ecological quality of rivers and the recreational behavior and associated values of visitors. Here we have to allow that there may well not be a simple linear relation between chlorophyll-*a* concentrations and the water quality perceived by recreational visitors (Hunter et al. 2012). To bridge this objective-subjective gap we use a tried and tested 'water quality ladder' (WQL), as developed by Hime et al. (2009). This links μg/l measures of chlorophyll-*a* concentrations and corresponding flora and fauna to a simple four level description of water quality (similar to the scale proposed by UKTAG (2008) for which Hime et al. (2009) provide a conversion table). This scale has been shown to significantly determine individuals' preferences and willingness to pay for river quality in separate stated preference studies of the Aire and various European rivers (Bateman et al., 2011). Table 4 provides ecological quality descriptions for the WQL and a summary of related recreational activities.

Table 4: Water quality classifications

WQL quality	Ecological Description	Chlorophyll-*a* Threshold (μg/l)	Recreational activities	Flora and fauna
Pristine	Oligotrophic	<4	Fishing, boating & swimming	No algae, all species of fish (game and coarse), water plants and birds, no water turbidity.
Good	Mesotrophic	4-10	Fishing, boating & swimming	No algae, no game fish, many species of coarse fish, water plants and birds, some water turbidity.
Mixed	Eutrophic	10-25	Fishing and boating	Some algae, no game fish, fewer species of coarse fish, water plants and birds. High water turbidity.
Poor	Hyper-eutrophic	>25	None	High levels of algae, no fish, no or few water plants or birds. Highest levels of water turbidity.

Source: Hime et al. (2009).

We applied our ecological quality model (Table 3) to predict water quality under the present and future climate scenario. Information on likely changes to predictor variables under our stylized climate scenario was gathered through personal communications with staff at CEH, Wallingford. This suggested that a 1^{o}C rise in air temperature may cause a greater than proportional increase in water temperature. Note that we assume rainfall to remain fixed at the annual average level and, therefore, the base flow index remains unaltered. Finally, the levels of suspended sediment are assumed to increase by 10%.

Table 5 details predicted water quality under the present and future climate scenario. Comparison of chlorophyll-*a* measures shows that at all three monitoring points we project a decline in future ecological quality arising from both the direct effect of water temperature increases and higher levels of nutrient loading arising from the climate-induced shift in land use. In relative terms this decline is greatest at the upper levels of water quality, where we see a downward shift from pristine to good quality on the WQL scale. In absolute terms, the increase in chlorophyll-*a* is greatest at lower levels of water quality. However, these are less marked in relative terms and do not breech the boundaries of respective WQL classes.

Table 5: Predicted reductions in water quality as a consequence of climate change.

Sub-catchment	**Present climate**		**Climate change scenario (+1ºC)**		**% increase in predicted Chlorophyll-*a***
	Predicted Chlorophyll-*a* (µg/l)	Corresponding WQL classification	Predicted Chlorophyll-*a* (µg/l)	Corresponding WQL classification	
A	3.39	Pristine	5.10	Good	50%
B	5.63	Good	7.81	Good	39%
C	11.95	Mixed	15.13	Mixed	27%

5. Recreation value impacts

The output of our ecological quality analysis forms an input to our assessment of the responsiveness of recreational values to the impacts induced by climate change. The key issue here is how the water quality changes predicted in Table 5 will affect visitation at sites which are available for recreational access.

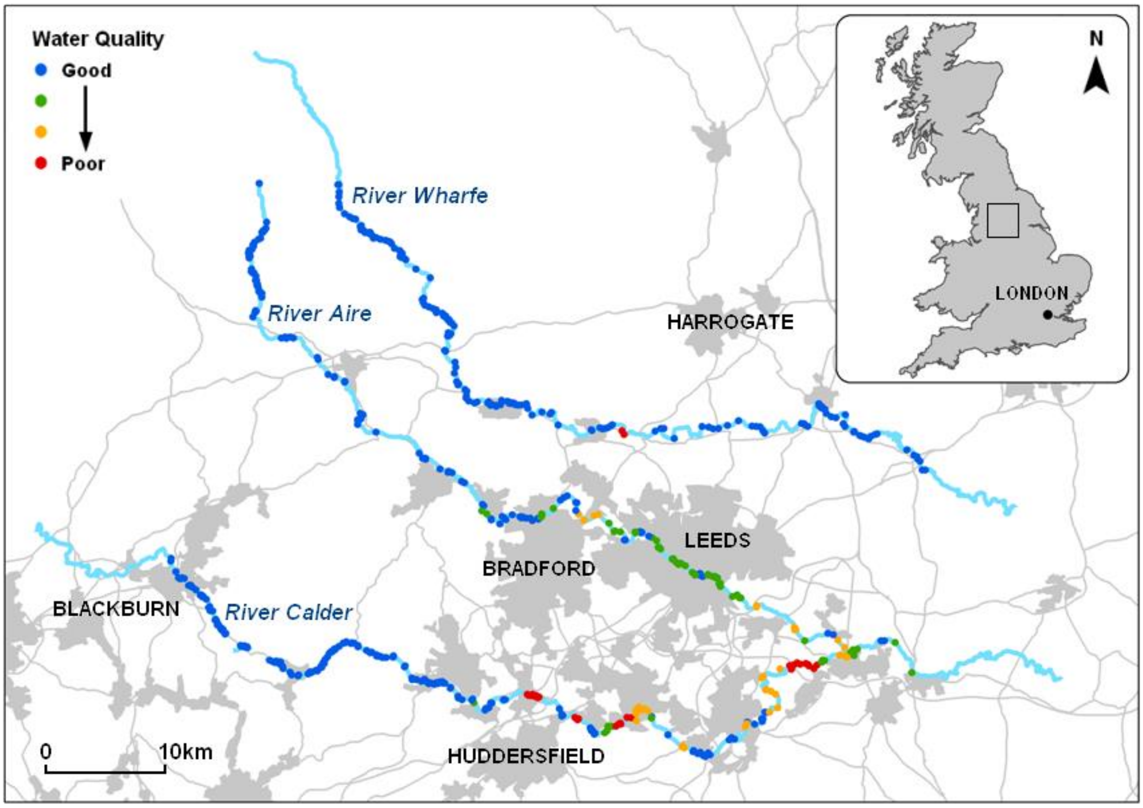
5.1 Sample survey and GIS data generation

A large sample survey of households was undertaken to estimate the recreational impact of changes in ecological quality. To capture the distance decay of values away from an improvement site (Bateman et al., 2006), a survey area was defined spanning a 70 km diameter centered on the River Aire, thereby embracing its catchment and surrounding areas. This helped to capture likely substitution effects generated by competing resources such as alternative rivers sites and other outdoor recreational opportunities.

The survey was explicitly designed to capture large quantities of spatially explicit data from respondents through a highly accessible custom built computer aided personal interview (CAPI) system. During the interview, respondents were shown an interactive map on a computer screen indicating the respondent's home location and all of the surrounding rivers within an area the same size as the full survey area. Respondents indicated on the map the river locations they visit for recreation and the frequency of their visits to each site. We also collected information regarding the total number of all outdoor trips taken in the last 12 months, within this the total number of visits to water bodies and detailed information about the river sites.

Once the interviews were completed, a GIS was used to match site visit locations to real world recreational sites using the four-step process described in the supplementary materials. In total, 531 recreational sites were identified along the studied rivers, which span approximately 230 km in length. The home location of each respondent was identified by linking Ordnance Survey Address Point data to the detailed geographical location information given by the full postcode provided by the respondent. Distance by road (as opposed to straight line) and travel time by car (adjusting for road quality, urban congestion, etc. using the methodology detailed by Bateman et al., 1996), from each respondent's home to each recreational site, including those not visited by the respondent, were calculated. This allowed us to examine the influence of the availability of substitute sites on the location and number of visits. Information on the environmental characteristics of the recreational sites was identified in the GIS using Ordnance Survey MasterMap and CEH Land Cover Map datasets. These provided details of the predominant land use around each of the recreational sites (e.g. urban). The current water quality at each of the river recreational sites was calculated from Environment Agency long-term water quality monitoring data and categorized into the four-point scale given in Hime et al. (2009), as illustrated in Figure 4.

Figure 4: Sampling area and the quality of river recreational access sites



After removing 2% of respondents due to missing address information or other item non-response from the survey sample, 1782 face-to-face at-home household interviews remained for analysis. Sample characteristics closely matched census data for the study catchment, with 44% of respondents being male, an average household size of 2.6 and average net income of £21,317 per annum (s.d. £11,700). In terms of occupation, 26% of respondents were in full time employment, 13% part-time employed, 33% retired and 7% self-employed with the remaining 21% not in employment.

The purpose of economic analyses of recreation choices is to reveal trade-offs between money and the availability and quality of natural resources. The random utility model (RUM) provides a standard approach for analyzing recreational behavior (Freeman et al., 2014). In the simplest multi-site model the only relevant information required is the site choice made by respondents.

However, a change in natural resource quality will affect not only the choice of sites but also the frequency of visits. To address this issue we implement a simplified version of the Morey et al. (1993) approach, as described below. Although there are numerous discrete formulations for modeling site choice, we use a specification which is widely adopted in the literature: the Conditional Logit Model (CLM) with alternative specific constant, based on McFadden (1974).

We specify the utility associated with visiting a recreation site as a function of access costs, water quality levels and other site characteristics. Following Hynes et al. (2009) we derive the travel cost as out-of-pocket expenditure (at a rate of £0.25 per km travelled round trip) plus the opportunity costs of time calculated as a percentage of the respondent's wage (Fezzi et al., 2014 suggests using 3/4 of the average wage rate).

Given the relatively short distance of the recreation sites from the respondents' houses, we assume that every day in a year might, in theory, provide a visit occasion (T=365). Within our sample, we observe the frequencies of visits to the 531 river access points, to other rivers in the sampling area, canals, lakes and other outdoor activities. Finally, we observe the number of times each individual decided not to take outdoor trips, giving that option the index $j=0$ (opt-out option). In this framework the individual i makes daily choices across the J options available (where $j=0,1, 2,\dots, 535$ within which $j=532,\dots,535$ represent visits to other rivers, canals, lakes and other outdoor trips). The individual chooses the option with the highest utility on each occasion. We define this utility U_{ijt} that respondent i in period t receives from a visit at site j as the random function:

$$U_{ijt} = v_{ijt} + \varepsilon_{ijt} = f(\boldsymbol{F_j}, \boldsymbol{G_{ij}}, \boldsymbol{\theta}) + \varepsilon_{ijt} \tag{6}$$

where $\boldsymbol{F_j}$ includes site characteristics that are constant across choice occasions and respondents, $\boldsymbol{G_{ij}}$ includes respondents' characteristics that change across sites, $\boldsymbol{\theta}$ is the parameter vector to be estimated, and ε_{ijt} is a random component that is unobservable to the analyst. This model posits that, given J recreation site options and the possibility of an opt-out, each respondent will choose either to recreate at the site that provides the highest random utility U_{ijt} (or not to recreate if this yields higher utility). Specifying a linear in parameters utility function, Equation (6) can be rewritten for each choice occasion as:

$$U_{ij=1,\dots,531} = \alpha_j + \boldsymbol{\eta}'\boldsymbol{F_j} + \boldsymbol{\beta}'\boldsymbol{G_{ij}}, + \varepsilon_{ij}, \text{ for each site within the sampling area} \tag{6.1}$$

$$U_{ij>531\ or\ j=0} = \alpha_j + \varepsilon_{ij}, \text{ for the other recreation options and the opt-out} \tag{6.2}$$

where θ=(α, $\boldsymbol{\beta}$, **η**). In this structure the utility of visiting sites other than the river stretches in our study area is captured by the alternative specific constant variables (α_j) and, for identification, the utility of not recreating is fixed to zero. Note, this latter choice also captures the utility of leisure and recreation opportunities other than those provided by outdoor trips.

Morey et al. (1993) formulate their repeated recreational choice model assuming that the error term is distributed as a Generalized Extreme Value random term. However, as demonstrated in Scarpa et al (2005) a similar approach is obtained using an Extreme Value type I error term with alternative specific constants:

$$\mathrm{P}\left[U_{ik} > U_{ij}\right] = \frac{e^{\alpha_k + \boldsymbol{\eta}'\mathbf{F}_k + \boldsymbol{\beta}'\mathbf{G}_{ik}}}{\sum_j e^{\alpha_j + \boldsymbol{\eta}'\mathbf{F}_j + \boldsymbol{\beta}'\mathbf{G}_{ij}}} \, . \qquad (7)$$

The model presents a globally concave likelihood function. Table 6 reports the description of variables and the parameter estimates, obtained via Maximum Likelihood. Note that the two lowest water quality levels (from Table 4) are merged into the category 'poor' while the 'pristine' level is set as the baseline. All variables in Table 6 are highly statistically significant and accord with prior expectations. The "travel cost" variable is significant and negatively signed as expected. The water quality variables are also significant and have expected negative signs indicating utility reductions from the baseline 'pristine' water quality. The positive sign on the "urban" parameter indicates that utility increases if the river site is in an urban area, suggesting that increasing the opportunity to utilize natural resources in highly populated areas might have a greater impact on welfare than in rural areas, possibly because of the lack of similar alternatives in everyday opportunities within cities. However, it is also possible that the positive sign on the urban parameter can be explained by correlations with other facilities available at river sites (e.g. car parks) and opportunities for complementing river recreation experiences with other types of outdoor recreation (e.g. taking children to playgrounds). All alternative specific constants present a negative sign, demonstrating the common sense finding that, over the year, respondents typically choose to spend their time on activities other than outdoor recreation.

Table 6: Estimated coefficients from travel cost model

Variable	Description	Coeff.	(Robust SE)
Travel cost	Two ways Travel cost defined as: out of pocket cost (0.25£ * km) + value of time	-0.16	(0.018)****
Good water quality	1=if site is good quality; 0 otherwise	-0.92	(0.234) **
Poor water quality	1=if site is below good quality (mixed or poor quality); 0 otherwise	-1.07	(0.221) ***
Urban	1=if the predominant land type around the site is urban; 0 otherwise	0.60	(0.14) ***
CSite	Alternative specific constant (ASC) river sites within the sampled area	-7.43	(0.226) ****
COthRiv	ASC for other river sites	-4.41	(0.129) ****
CCanal	ASC for canals	-3.81	(0.079) ****
Clake	ASC for lakes	-4.13	(0.093) ****
COthRe	ASC for other outdoor recreational sites	-2.80	(0.071) ****
LL	-488,258		

Note: "**" = t-stat > 3, "***" = t-stat > 4, "****" = t-stat > 10

Taking the estimated parameters from Table 6 and following, for example, Small and Rosen (1982) or Hanemann (1999), it is possible to derive the welfare impact of changes in water quality across a range of alternative scenarios.

6. Integrated Results

Using a highly spatially explicit GIS framework, we have introduced models to track the connections between climate change and induced changes in agricultural land use, river water quality and recreation demand. The current section presents an analysis at both the individual and catchment-wide scales for a simple climate change scenario of 1^{o}C warming. Here we illustrate how agricultural incomes and water quality are impacted and also how these changes in turn affect the value of river-based recreational activities within the case-study area.

6.1. Estimating individual level values for changes in the ecological quality of rivers.

The analyses developed above allow us to track how the direct effect of a 1^{o}C temperature rise, combined with the indirect impact of induced LUC and consequent alterations in diffuse pollution, would result in a decrease in water quality throughout the case study area. The same analysis suggests that this will in turn reduce the number of good quality water recreation sites.

To estimate the consequences of the climate change scenario we apply the changes in water quality predicted from our ecological model (Table 3) to the parameter estimates given in our travel cost model (Table 6). Results indicate that the average disutility generated by the expected loss in recreational quality, expressed as compensation required per year (i.e. negative WTP; see discussions in Horowitz and McConnell, 2002 and Bateman et al., 2009) is equal to £10.44 per person per annum in the case-study area. For decision purposes we then aggregate these individual estimates up to assess losses for the entire study area.

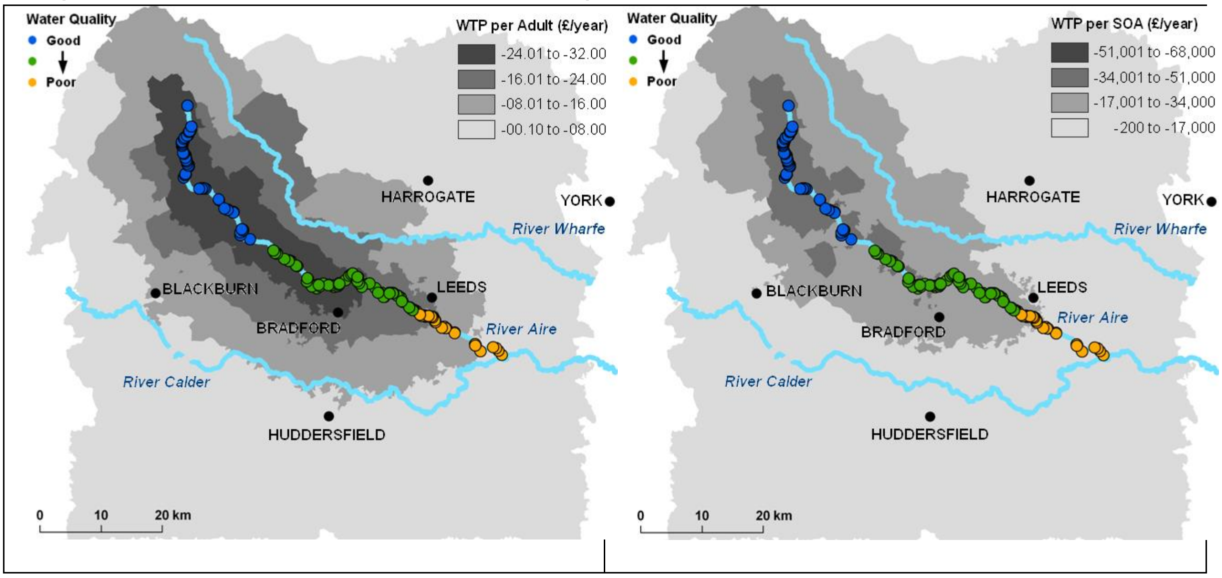
The Supplementary Materials to this paper assess the value of policy action to both mitigate these losses and attain pristine ecological and chemical status through full implementation of the EU Water Framework Directive (WFD) (European Commission, 2000).

6.2 Estimating aggregate level values for changes in the ecological quality of rivers.

In order to aggregate our recreation values we require distance calculations from all possible recreation sites to all households (not just those sampled in our survey) within the study area. We also require socioeconomic characteristics for all households to allow for variations in wage rate within the travel cost calculation. Our GIS-based methodology allows us to perform these calculations with minimal simplification, working, in this instance, with UK Census Super Output Areas (SOAs).

The spatial distribution of changes in recreation values under the climate change scenario is illustrated in Figure 5. Here the left hand panel presents the distribution of changes in per person values while the SOA aggregated values are given in the right hand panel. The site colors illustrate the estimated quality in the baseline situation. The climate change scenario induces a reduction in water quality along the length of the River Aire although impacts are most marked in the western area of the catchment, where quality declines from Pristine (sites shown as blue in Figure 5) to Good quality. Aggregating across the entire case study area yields an estimate of the total loss in recreation value induced by climate change of approximately £26 million p.a. These losses, as one might expect, are concentrated in the western area of the catchment. Although population is relatively low here, this is the principal location where declines in water quality occur. The eastern area of the catchment does not suffer such an appreciable decline and, therefore, its aggregate values are relatively low.

Figure 5: The spatial distribution of per person (left hand panel) and SOA aggregate (right hand panel) changes in recreation value under the climate change scenario.



Notes: Colors represent predicted site qualities in the baseline scenario where: blue = Pristine; green = Good; yellow = Mixed. Under the climate change scenario, water quality at all currently Pristine sites declines to Good quality. Water quality is as follows: blue = Pristine; green = Good; yellow = Mixed; red = Poor. Water quality definitions given in Table 4.

Figure 5 suggests that climate change effects present spatially heterogeneous welfare impacts which should not be ignored if we wish to ensure efficient allocation of resources to mitigate impacts. However, policies, such as the WFD, tend to ignore the spatial distribution of benefits such that funds are spent in an untargeted and inefficient manner resulting in resources generating highly variable net benefits.

7. Conclusions.

We present a unified series of models examining the direct, secondary and further effects of a given driver acting upon natural capital resources. The specific case study concerns the impact of climate change upon agricultural profitability, inducing shifts in land use and consequent impacts upon diffuse pollution, water and ecological quality and the recreational value of affected waterways. We model each of these relationships and calculate the resultant impact upon non-market recreational values. In so doing we demonstrate the use of spatial analytic techniques for incorporating biophysical data within environmental economic analyses.

In line with previous research (e.g. Fezzi et al., 2015; Fezzi and Bateman, 2015), results show that climate change is likely to generate spatially variable impacts upon both land use and resulting farm incomes. In some areas, it will generate income gains while other areas will experience losses. This pattern directly reflects the diverse and heterogeneous nature of UK agriculture. While acknowledging that the direct market impacts of climate change on UK agriculture may generally be positive, a central contribution of this research has been to demonstrate that focusing solely on these direct impacts paints a highly incomplete picture of the net impact of climate change. In our case study of the UK's River Aire, climate change both directly and via induced agricultural LUC yields a general decline in ecological quality which in turn reduces recreational values substantially.

The complexity of human-environment relationships means that examining only direct impacts may well be insufficient in order to guide efficient policy making. Research needs to extend analyses to embrace all major consequences of change. Depending upon the case study in question, this may require substantial integration of data, modeling and analytical techniques as well as a willingness to combine natural science, social science and economic perspective. No single discipline is sufficient to tackle the challenge of integrated environmental-economic decision making.

The modular nature of our methodology means that it can be readily extended. The agricultural, hydrological and recreation models presented here can easily be updated as improved versions become available. Moreover, the approach is highly suitable for extension to incorporate additional elements describing impacts on, say, greenhouse gases and biodiversity, or natural hazard and flood risk while expansion to cover alternative or wider geographic areas is straightforward (Bateman et al., 2013). An interesting and timely extension would be to consider how recent policy changes (e.g. WFD or Common Agricultural Policy) interact with climate change to drive on-farm decision making and the subsequent impacts. While complex, we believe that such methodologies are vital to addressing the complexities of the real world and bring them within the remit of economic analysis.

Finally, some caution is needed in interpreting our results. We used a simplified climate scenario for illustrative purposes. Future research should incorporate more sophisticated climate models and also account for seasonal variation. Moreover, timescale is an important element of the relationship between land use change and water quality. Given the interactions with groundwater reservoirs, there is some lag between land use change and impacts on water quality (Hutchins et al., 2010a; Stalnacke et al., 2004) and, therefore, the direct effect of climate on water environments may arise considerably later or last longer. Another important area for further development is considering measures of uncertainty. Our approach, being a fully statistical and econometric approach, can be used to produce confidence intervals for all the estimates and explore how uncertainty propagates throughout the models via Monte Carlo simulation. While this issue has not been explored in the present analysis, it is certainly a promising avenue for further research.

Acknowledgements

The authors acknowledge funding from the European Commission Seventh Framework Programme under Grant Agreement No. FP7-ENV-2012-308393-2 (OPERAs); and the Water Economics, Policy and Governance Network (WEPGN), funded by a Social Sciences and Humanities Research Council (SSHRC) Partnership Grant.

References

Amemiya, Takeshi (1973) Regression analysis when the dependent variable is truncated normal, *Econometrica*, 41, 997–1016, DOI: 10.2307/1914031

Bateman, I.J., Brouwer, R., Ferrini, S., Schaafsma, M., Barton, D.N., Dubgaard, A., Hasler, B., Hime, S., Liekens, I., Navrud, S., De Nocker, L., Ščeponavičiūtė, R., and Semėnienė, D. (2011) Making benefit transfers work: Deriving and testing principles for value transfers for similar and dissimilar sites using a case study of the non-market benefits of water quality improvements across Europe, *Env. & Res. Econ.* 50(3): 356-387, DOI 10.1007/s10640-011-9476-8.

Bateman, I.J., Day, B.H, Agarwala, M., Bacon, P., Bad'ura, T., Binner, A., De-Gol, A., Ditchburn, B., Dugdale, S., Emmett, B., Ferrini, S., Fezzi, C., Harwood, A., Hillier, J., Hiscock, K., Hulme, M., Jackson, B., Lovett, A., Mackie, E., Matthews, R., Sen, A., Siriwardena, G., Smith, P., Snowdon, P., Sünnenberg, G., Vetter, S., & Vinjili, S. (2014) *Economic value of ecosystem services*, UK National Ecosystem Assessment Follow-on, UNEP-WCMC, LWEC, UK.

Bateman, I.J., Day, B.H., Georgiou, S. and Lake, I. (2006) The aggregation of environmental benefit values: Welfare measures, distance decay and total WTP. *Ecol. Econ*. 60(2): 450-460, doi:10.1016/j.ecolecon.2006.04.003.

Bateman, I.J., Day, B.H., Jones, A. P. and Jude, S. (2009) Reducing gains/loss asymmetry: A virtual reality choice experiment (VRCE) valuing land use change, *J. Env. Econ. & Man.* 58: 106-118, doi:10.1016/j.jeem.2008.05.003

Bateman, I.J., Garrod, G.D., Brainard, J.S. and Lovett, A.A. (1996) Measurement, valuation and estimation issues in the travel cost method: A geographical information systems approach, *J. Agric. Econ.* 47(2): 191-205, DOI: 10.1111/j.1477-9552.1996.tb00684.x

Bateman, I., Harwood, A., Mace, G., Watson, S. R., Abson, D. J., Andrews, B., Binner, A., Crowe, A., Day, B., Dugdale, S., Fezzi, C., Foden, J., Hadley, D., Haines-Young, R., Hulme, M., Kontoleon, A., Lovett, A., Munday, P., Pascual, U., Paterson, J., Perino, G., Sen, A., Siriwardena, G., Van Soest, D., Termansen, M. (2013) Bringing Ecosystem Services into Economic Decision-Making: Land Use in the United Kingdom. *Science* 341(6141): 45-50. DOI: 10.1126/science.1234379

Bateman, I.J., Jones, A.P., Lovett, A.A., Lake, I. and Day B.H. (2002) Applying geographical information systems (GIS) to environmental and resource economics, *Env. & Res. Econ.* 22(1-2): 219-269. DOI: 10.1023/A:1015575214292

Bateman, I.J., Lovett, A.A. and Brainard, J.S. (2003) *Applied Environmental Economics: a GIS Approach to Cost-Benefit Analysis*, Cambridge University Press, Cambridge.

Bennett E.M., Peterson G.D. & Gordon L.J. (2009). Understanding relationships among multiple ecosystem services. *Ecol. Lett.* 12, 1394-404. doi: 10.1111/j.1461-0248.2009.01387.x

Boyer J.N., Kelble C.R., Ortner P.B., and Rudnik D.T. (2009) Phytoplankton bloom status: Chlorophyll a biomass as an indicator of water quality condition in the southern estuaries of Florida, USA, *Ecol. Indic.* 9(6): S56–S67. doi:10.1016/j.ecolind.2008.11.013

Boyd, J. and Banzhaf, S. (2007) What are ecosystem services? The need for standardized environmental accounting units. *Ecol. Econ.* 63: 616–626, doi:10.1016/j.ecolecon.2007.01.002.

Crowther, J., Hampson, D., Bateman, I.J., Kay, D., Posen, P., Stapleton, C. M., and Wyer, M. D. (2011) Generic modelling of faecal indicator organism concentrations in the UK, *Water*, 3: 682-701; doi:10.3390/w3020682

Cullen J.J. (1982) The deep chlorophyll maximum comparing vertical profiles of chlorophyll a., *Canadian J. Fish.& Aquatic Sci.*, 39: 791–803, doi:10.1139/f82-108

Davies HN, Neal C. 2007. Estimating nutrient concentrations from catchment characteristics. *Hydr. & Earth Sys. Sci.*, 11: 550–558, http://www.hydrol-earth-syst-sci.net/11/550/2007/hess-11-550-2007.html

de Bello F., Lavorel S., Díaz S., Harrington R., Cornelissen J.C., Bardgett R., Berg M., Cipriotti P., Feld C., Hering D., Martins da Silva P., Potts S., Sandin L., Sousa J., Storkey J., Wardle D. & Harrison P. (2010). Towards an assessment of multiple ecosystem processes and services via functional traits. *Biodivers Conserv*, 19, 2873-2893, DOI 10.1007/s10531-010-9850-9.

de Groot, R.S., Wilson, M.A., and Boumans, R.M.J. 2002. A typology for the classification, description and valuation of ecosystem functions, goods and services. *Ecol. Econ.* 41: 393–408, doi:10.1016/S0921-8009(02)00089-7

Ebbert, J.C., Embrey, S.S. and Kelley, J.A. (2005) Concentrations and Loads of Suspended Sediment and Nutrients in Surface Water of the Yakima River Basin, Washington, 1999-2000 - With an Analysis of Trends in Concentrations, *Water-Resources Investigations Report 03-4026*, USGS National Water-Quality Assessment Program, U.S. Geological Survey, Reston, Virginia, http://pubs.usgs.gov/wri/wri034026/

European Commission (2000). Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for the Community action in the field of water policy. *Off. J. Euro. Comm.* Vol 43, http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32000L0060

Fezzi, C. and Bateman, I.J. (2011) Structural agricultural land use modeling for spatial agro-environmental policy analysis, *Am. J. Agric. Econ.* 93 (4): 1168-1188, doi: 10.1093/ajae/aar037

Fezzi, C. and Bateman, I. (2015) The impact of climate change on agriculture: Nonlinear effects and aggregation bias in Ricardian models of farmland values. *J. Ass. Env.& Res. Econ.* 2(1): 57-92. Doi: 10.1086/680257.

Fezzi C., Bateman I.J., Askew T., Munday P., Sen A., Harwood A. (2014) Valuing provisioning ecosystem services in agriculture: the impact of climate change on food production in the United Kingdom, *Env. & Res. Econ.*, 57(2): 197-214, DOI 10.1007/s10640-013-9663-x

Fezzi C., Bateman I.J., Ferrini S. (2014) Using revealed preferences to estimate the value of travel time to recreation sites, *J. Env. Econ. & Man.*, 67:58–70, http://dx.doi.org/10.1016/j.jeem.2013.10.003

Fezzi, C., Hutchins, M., Rigby, D., Bateman, I.J., Posen, P. and Hadley, D., (2010) Integrated Assessment of Water Framework Directive Nitrate Reduction Measures, *Agric. Econ.* 41(2): 123–134, DOI: 10.1111/j.1574-0862.2009.00430.x

Fezzi C., Rigby D., Bateman I.J., Hadley D., Posen P. (2008) Estimating the range of economic impacts on farms of nutrient leaching reduction policies, *Agric. Econ.*, 39(2): 197-205, DOI: 10.1111/j.1574-0862.2008.00323.x.

Fezzi C., Harwood A., Lovett A., Bateman I.J. (2015) The environmental impact of climate change adaptation on land use and water quality, *Nature Climate Change*, 5, 255–260, doi:10.1038/nclimate2525. Fisher, B., Turner, R.K., Zylstra, M., Brouwer, R., de Groot, R., Farber, S., Ferraro, P., Green, R., Hadley, D., Harlow, J., Jefferiss, P., Kirkby, C., Morling, P., Mowatt, S., Naidoo, R., Paavola, J., Strassburg, B., Yu, D. and Balmford, A. (2008) Ecosystem services and economic theory: integration for policy-relevant research. *Ecol. App.*, 18(8): 2050–2067, doi: 10.1890/07-1537.1

Fisher, B. and Turner, R.K. (2008) Ecosystem services: classification for valuation. *Biol. Cons.* 141(5): 1167–1169. doi:10.1016/j.biocon.2008.02.019

Freeman A.M. III., Herriges, J.A., Kling, C.L. (2014) *The Measurement of Environmental and Resource Values: Theory and Methods*, RFF Press, Routledge, New York.

Goldstein, J.H., Caldarone, G. Duarte T.K, Ennaanay, D., Hannahs, N., Mendoza, G., Polasky, S., Wolny, S. and Daily G.C. (2012). Integrating ecosystem-service tradeoffs into land-use decisions. *PNAS*, 109 (19): 7565–7570, doi: 10.1073/pnas.1201040109.

Guerry, A.D., Polasky, S., Lubchenco, J., Chaplin-Kramer, R., Daily, G.C., Griffin, R., Ruckelshaus, M.H., Bateman, I.J., Duraiappah, A., Elmqvist, T., Feldman, M.W., Folke, C., Hoekstram, J., Kareiva, P., Keeler, B., Li, S., McKenzie, E., Ouyang, Z., Reyers, B., Ricketts, T., Rockström, J., Tallis, H. and Vira, B. (2015) Natural capital informing decisions: from promise to practice, *PNAS*, 112 (24) 7348–7355, www.pnas.org/cgi/doi/10.1073/pnas.1503751112

Hanemann W.M., 1999. Welfare analysis with discrete choice models, in Herriges J. and Kling C. (eds.) *Valuing Recreation and the Environment*. Cheltenham, UK and Northampton, MA: Edward Elgar.

Hime, S., Bateman, I., Posen, P., Hutchins, M. (2009). A transferable water quality ladder for conveying use and ecological information within public surveys. *CSERGE working paper EDM-2009-01*. http://www.uea.ac.uk/env/cserge/pub/wp/edm/edm_2009_01.htm

Horowitz, J. K., McConnell, K. E. (2002) A Review of WTA / WTP Studies, *J. Env. Econ. & Man.*, 44(3): 426-447. doi:10.1006/jeem.2001.1215

Hunter, P.D., Hanley, N., Czajkowski, M., Mearns, K., Tyler, A.N., Carvalho, L., Codd, G.A. (2012) The effect of risk perception on public preferences and willingness to pay for reductions in the health risks posed by toxic cyanobacterial blooms. *Sci. Tot. Env.* 426, 32-44, doi: 10.1016/j.scitotenv.2012.02.017.

Hutchins, M., Fezzi, C., Bateman, I.J., Posen, P. and Deflandre-Vlandas, A. (2009) Cost-Effective Mitigation of Diffuse Pollution: Setting Criteria for River Basin Management at Multiple Locations, *Env. Man.*, 44(2): 256-267. DOI 10.1007/s00267-009-9306-8.

Hutchins M.G., Deflandre-Vlandas, A., Posen, P., Davies, H. (2010a) How do river nitrate concentrations respond to changes in land-use? A modelling case study of headwaters in the River Derwent catchment, North Yorkshire UK. *Environ Model Assess*, 15: 93-109, DOI 10.1007/s10666-009-9218-2

Hutchins M.G., Johnson, A., Deflandre-Vlandas, A., Comber, S., Posen, P., Boorman, D.B., (2010b) Which offers more scope to suppress river phytoplankton blooms: reducing nutrient pollution or riparian shading? *Sci. Tot. Env.* 408: 5065-5077.

Hynes, S., Hanley, N., O'Donoghue, C. (2009) Alternative treatments of the cost of time in recreational demand models: an application to whitewater kayaking in Ireland. *J. Env. Man.* 90(2), 1014-1021. doi:10.1016/j.jenvman.2008.03.010

Jackson, B., Pagella, T., Sinclair, F., Orellana, B., Henshaw, A., Reynolds, B., Mcintyre, N., Wheater, H., Eycott, A., (2013) Polyscape: A GIS mapping framework providing efficient and spatially explicit landscape-scale valuation of multiple ecosystem services, *Land. & Urb. Plan.* 112: 74-88. doi:10.1016/j.landurbplan.2012.12.014

Kahneman, Daniel, Jack L. Knetsch and Richard H. Thaler (1990). Experimental tests of the endowment effect and the Coase theorem. *J. Pol. Econ.* 98(6): 1325-1348, http://www.jstor.org/stable/2937761

Lamarque P., Lavorel S., Mouchet M. & Quétier F. (2014). Plant trait-based models identify direct and indirect effects of climate change on bundles of grassland ecosystem services. *PNAS*, 111, 13751-13756, doi: 10.1073/pnas.1216051111

Lawler, J. J., Lewis, D. J., Nelson, E., Plantinga, A. J., Polasky, S., Withey, J. C., Helmers, D.P., Martinuzzi, S., Pennington, D. and Radeloff, V. C. (2014). Projected land-use change impacts on ecosystem services in the United States. *PNAS*, 111(20), 7492–7497. http://doi.org/10.1073/pnas.1405557111

Lord, E. I., S. G. Anthony, and G. Goodlass. (2002) Agricultural nitrogen balance and water quality in the UK, *Soil Use and Management*, 18(4): 363–369, DOI: 10.1111/j.1475-2743.2002.tb00253.x.

McFadden, D. (1974) The measurement of urban travel demand. *J. Pub. Econ.* 3, 303-328, http://www.sciencedirect.com/science/article/pii/0047-2727(74)90003-6

Milne, E., Aspinall, R.J. and Veldkamp, T.A. (2009) Integrated modelling of natural and social systems in land change science, *Land. Ecol.*, 24(9): 1145-1147, DOI: 10.1007/s10980-009-9392-2

Morey, E.R., Rowe, R.D., Watson, M. (1993) A Repeated Nested-Logit Model of Atlantic Salmon Fishing. *Am. J. Agri. Econ.* 75(3), 578-592, doi: 10.2307/1243565

Nelson E., Mendoza G., Regetz J., Polasky S., Tallis H., Cameron D., Chan K.M.A., Daily G.C., Goldstein J., Kareiva P.M., Lonsdorf E., Naidoo R., Ricketts T.H. & Shaw M. (2009) Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. *Front. Ecol. Env.*, 7(1): 4-11, 10.1890/080023.

Posen, P., Hutchins, M., Lovett, A., Davies, H. (2011) Identifying the catchment size at which robust estimations of agricultural land use can be made, and implications for diffuse pollution modelling. *App. Geog.*, 31(3): 919-929, doi:10.1016/j.apgeog.2011.01.021 Pudney S. (1989) *Modelling individual choice: the econometrics of corners, kinks and holes*, Blackwell Publishers, Cambridge.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E.F., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J. (2009) A safe operating space for humanity. *Nature* 461, 472-475, doi:10.1038/461472a.

Scarpa R., Ferrini S., Willis K., (2005). Performance of error component models for status-quo effects in choice experiments. In Alberini A., Scarpa R. (Eds.) *Applications of simulation methods in environmental and resource economics*. Springer Netherlands: 247-273.

Small K.A., Rosen H.S., (1981) Applied Welfare Economics with Discrete Choice Models, *Econometrica*, 49(1)105-130, DOI: 10.2307/1911129.

Stalnacke, P., Vandsemb, S. M., Vassiljev, A., Grimvall, A., and Jolanki, G. (2004) Changes in nutrient levels in some Eastern European rivers in response to large-scale changes in agriculture. *Water Sci. & Tech.* 49: 29-36, http://www.ncbi.nlm.nih.gov/pubmed/15053096.

Tobin J. (1958) Estimation for relationships with limited dependent variables, *Econometrica,* 26(1): 24–36, DOI: 10.2307/1907382.

Train, K. 2003. *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press.

UKCP (UK Climate Projections) (2009) *UKCP09*, available at http://ukclimateprojections.defra.gov.uk/

UK Technical Advisory Group (UKTAG) – Water Framework Directive (2008) *Phase 1 Report - Environmental standards and conditions for surface waters*. Available from http://www.wfduk.org/UK_Environmental_Standards/LibraryPublicDocs/UKTAG%20ReportAug%202006UKEnvironmentalStandardsandConditionsFinalReport

van Delden, H., Van Vliet, J., Rutledge, D. T., & Kirkby, M. J. (2011). Comparison of scale and scaling issues in integrated land-use models for policy support. *Agri Ecos. & Env.*, 142(1-2), 18-28, doi:10.1016/j.agee.2011.03.005.

Wallace, K.J. (2007). Classification of ecosystem services: problems and solutions. *Biol. Cons*. 139(3-4): 235–246, doi:10.1016/j.biocon.2007.07.015.

White, H. (1980) A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica*, 48(4), 817-838. Doi: 10.2307/1912934

Whitehead, P.G., Crossman, J., Balana, B.B., Futter, M.N., Comber, S., Jin, L., Skuras, D., Wade, A.J., Bowes, M.J., Read, D.S., 2013. A cost-effectiveness analysis of water security and water quality: impacts of climate and land-use change on the River Thames system. *Philos. Trans. A. Math. Phys. Eng. Sci*. 371, 20120413. doi:10.1098/rsta.2012.0413

Yen S.T., Huang C.L. (2002) Cross-sectional estimation of U.S. demand for beef products: a censored system approach, *J. Agri. & Res. Econ.* 27(2): 320-334, http://purl.umn.edu/31124.

Supplementary Materials for

Spatially explicit integrated modeling and economic valuation of climate driven land use change and its indirect effects

Ian Bateman, Amy Binner, Brett Day, Silvia Ferrini, Carlo Fezzi,
Michael Hutchins, Matthew Agarwala, Emma Coombes, Andrew Lovett, Paulette Posen.

SM1: The agricultural land use model

Table SM1 presents descriptive statistics of land uses and livestock numbers for three illustrative years and for the total dataset.

Table SM1: Descriptive statistics, land uses (ha) and livestock numbers (head) per 2km^2 grid square

	1969	1988	2004	Total			
	$\bar{x}$	$\bar{x}$	$\bar{x}$	$\bar{x}$	$\hat{s}(x)$	Min	Max
Cereals	87.8	94.6	76.4	83.0	77.4	0	347
Oilseed Rape	0.1	8.5	13.3	6.9	12.3	0	125
Root crops	10.1	9.5	7.5	9.1	18.7	0	187
Temp. grassland	41.1	28.8	22.6	29.3	28.7	0	349
Perm. grassland	116.7	115.6	112.7	113.0	97.0	0	400
Rough grazing	47.1	39.6	40.5	44.0	100.0	0	400
Other	22.8	26.6	45.7	37.8	45.6	0	400
Total land	325.6	323.2	318.7	323.1	96.9	1.25	400
Dairy	87.1	71.5	62.0	74.1	99.1	0	1128
Beef	151.4	149.8	89.9	144.9	123.8	0	1221
Sheep	472.2	784.1	323.8	693.6	899.0	0	11289

Notes: Only grid squares containing some agricultural land are considered, $\bar{x}$ indicates the sample mean, $\hat{s}(x)$ the sample standard deviation.

SM1.1: Data sources

In order to correctly assess the financial, policy and environmental drivers of land use change, our agricultural land use analysis employs a unique database, which integrates multiple sources of information dating back to the late 1960s. The resulting data, collected at a 2 km^2 grid square (400 ha) resolution, cover the whole of England and Wales and encompass, for the past 40 years: (a) land use shares and livestock numbers, (b) environmental and climatic determinants, (c) input and output prices, (d) policy and other drivers. However, we do not include yield and profits data, since the necessary information is not available at the disaggregated level required by this analysis.

Agricultural land use and livestock values, collected by the Department for Environment, Food and Rural Affairs (Defra) and the Welsh Government (formerly Welsh Assembly Government), were derived from the June Agricultural Census (JAC) aggregated at a 2 km^2 resolution by EDINA (www.edina.ac.uk). These data are available for England and Wales for seventeen (non-consecutive) years between 1969 and 2006 (only Welsh data are available for 2005 and 2006). This yields roughly 38,000 grid-square records each year. In terms of livestock numbers, we distinguish between dairy cattle, beef cattle and sheep. For agricultural land use types, we explicitly model cereals (including wheat, barley, oats, etc.), oilseed rape, root crops (potatoes and sugar beet), temporary grassland (grass sown every 3 to 5 years and typically part of an arable crop rotation), permanent grassland (grassland maintained perpetually without reseeding) and rough grazing. These six land use types together account for more than 88% of the total agricultural land in England and Wales. We include the remaining 12% in an "other" land category encompassing horticulture, other arable crops, on-farm woodland, set-aside, bare fallow and all other land (ponds, paths, etc.).

Environmental determinants are described in the main paper. Regarding price data, there was no unique source that supplied the necessary comprehensive database for the United Kingdom. Therefore, we compiled a new database by extracting time-series data from a variety of different sources, linked by data from common years. Cereals price is based on the simple average of wheat, barley, and oats prices, derived from DEFRA (2006), the Ministry of Agriculture, Fisheries and Food (MAFF, 1986), and Mitchell (1988). Root crops price is given by the average of potatoes and sugar beet prices, extracted from DEFRA (2006), MAFF (1986), and the Office of National Statistics (ONS; 1974–1985), the same sources being used for the oilseed rape price. Milk, dairy cattle, beef meat (per cow), and lamb meat (per sheep) prices are based on DEFRA (2006) and ONS (1974–1985). Fertilizer price is derived from DEFRA (2006) and ONS (1974–1985); oil price from the British Petroleum Statistical Review of World Energy; and milk quota (leased) prices from Ian Potter Associates (www.ipaquotas.com). Rather than using actual output prices in each year, we use expected output prices, defined as the predictions of an autoregressive model of order one, AR(1), with trend.

SM1.2: Estimation procedure

Since micro-data on land use are typically censored (farms are very unlikely to comprise some element of all possible land uses) assuming normal disturbances and implementing ML leads to inconsistent estimates of the land use shares and input and output intensity equations (Amemiya, 1973). We address this issue by specifying a Tobit system of equations (Tobin, 1958) and, following Pudney (1989), treat one of the shares as a residual category, defined by the identity:

(6) $s_h = 1 - \sum_{j=1}^{h-1} s_j$,

and estimating the remaining h – 1 equations as a joint system. When the number of equations is higher than three the ML estimation of a Tobit system requires the evaluation of multiple

Gaussian integrals which is computationally extremely intensive. In this paper we follow the practical and computationally feasible solution proposed by Yen et al. (2003), who suggest approximating the multivariate Tobit with a sequence of bivariate models, deriving a consistent Quasi Maximum Likelihood (QML) estimator (detailed in Fezzi and Bateman, 2011). We also account for possible heteroskedasticity in the error term allowing the standard errors to vary across observations as a function of a vector of exogenous variables. This QML estimator is consistent, allows the estimation of cross-equation correlations and the imposition of cross-equation restrictions. The model includes regional and annual fixed effects to capture the potential differences of technological and labor cost changes and other omitted variables.

SM2: Identification of potential recreational visit sites.

Recreational visit data were collected via a household survey using a highly accessible, custom built, computer-aided personal interview (CAPI) system. This considerably reduced the cognitive load on respondents when being asked about recreational activities by presenting an interactive map on which she/he could point and click to denote all visited river sites. For each site, details on number of visits, activities, etc., were collected. Demand for water related recreation was modeled using information on the total number of outdoor trips taken during the previous 12 months, frequency of trips to water bodies, facility and quality information about the river sites and respondent data on visits to other recreational sites.

Visit site locations were matched to real world recreational sites using GIS software (ArcGIS v9.2, ESRI) as follows:

1. River stretches that are accessible to the public (defined as those river stretches which have either a public footpath or minor road within 50 m) were identified.

2. These publicly-accessible river stretches were assigned access points by identifying where the footpath or road first joined or met these stretches.

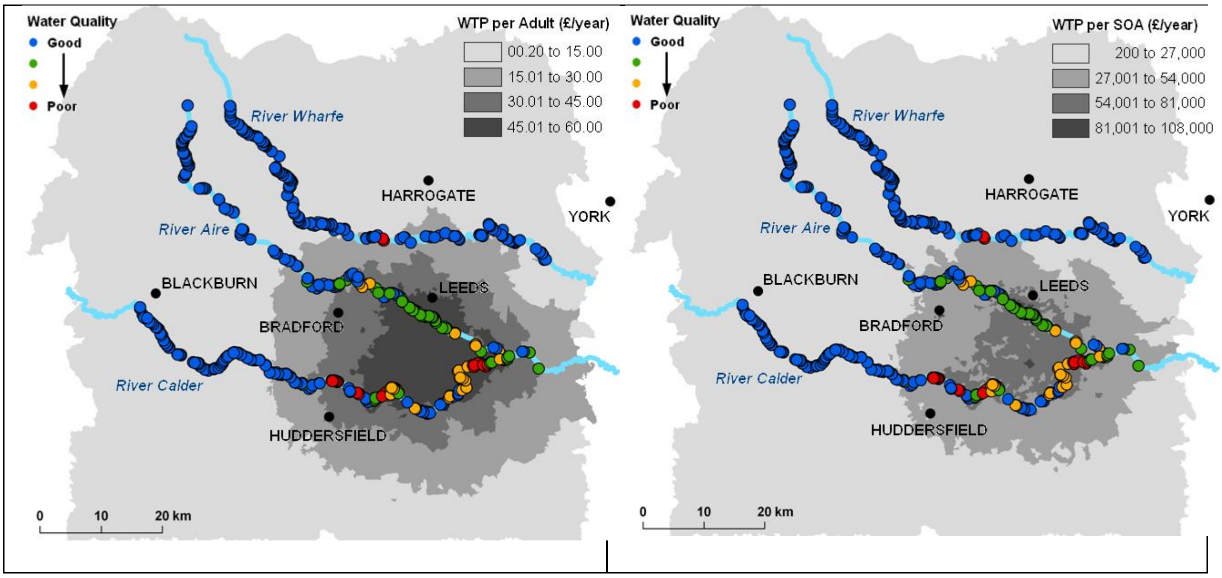
3. Where access points were extremely close together (i.e. within 150 m of each other) and had similar environmental characteristics, they were grouped together to form a single recreational site.

4. The locations of each of the recreational sites were verified using Ordnance Survey 1:50,000 maps and aerial photographs.

SM3: Analysis of a mitigation policy – Implementing the WFD

The losses likely to occur under climate change will of course be mitigated to a smaller or greater extent by the degree of policy intervention undertaken. One possible mitigation strategy is provided by implementation of the Water Framework Directive (WFD) (European Commission, 2000) which requires member states of the European Union (EU) to avoid any reduction in water quality and instead act to raise freshwaters to pristine quality (European Commission, 2000). Starting from the current baseline, raising all sites along the length of the River Aire to pristine quality would deliver average annual recreational benefits of £17.89 per person p.a. The spatial distribution of benefits is illustrated in Figure SM1 (with the per person values shown in the left hand panel and the per SOA aggregation given in the right hand panel) and is crucial in determining aggregate values. Those sites which would benefit most from implementation of the WFD are in the downstream (eastern) reaches of the river where water quality would be increased from Mixed (sites shown as yellow dots) or Good (sites shown as green dots) to Pristine quality, whereas in the upstream (western) stretches of the river implementation of the WFD holds the quality at Pristine (blue dots) rather than allowing it to decline. The aggregate value of these changes is considerably boosted by the fact that the eastern catchment not only gains the most in terms of water quality but is also far more densely populated than the west. These factors combine to generate total benefits from implementing the WFD of approximately £65 million p.a. These contrast with annual losses of £10.44 per person and £26 million in aggregate arising from the climate change scenario considered in the main paper.

Figure SM1: The distribution of per person (left hand panel) and SOA aggregate (right hand panel) value changes for the WFD policy.



Notes: Dots show observed water quality site in the baseline scenario (providing a contrast with predicted baseline quality as illustrated in Figure 5). Water quality is as follows: blue = Pristine; green = Good; yellow = Mixed; red = Poor (quality defined in Table 4).

These case studies clearly demonstrate the importance of considering the spatial distribution of benefits in assessing the value of policy interventions. Equally importantly, while we do not consider the full costs of implementing the WFD, the substantial benefits it delivers suggests that it may well yield overall gains. Analyses of alternative approaches to reducing diffuse agricultural pollution suggest that there is no necessary correlation between the cost of measures and their effectiveness. For example simple buffer strips have been found to be highly effective in mitigating the transport of farm fecal matter into water courses (Hampson et al., 2010).

References for Supplementary Materials

Amemiya, T. 1973. Regression analysis when the dependent variable is truncated normal. *Econometrica* 41: 997–1016, DOI: 10.2307/1914031

DEFRA. 2006. *Agriculture in the United Kingdom 2005*. Joint report by DEFRA, the Scottish Executive Environment and Rural Affairs Department, the Department of Agriculture and Rural Development (Northern Ireland), and the Welsh Assembly Government. https://www.gov.uk/government/collections/agriculture-in-the-united-kingdom (accessed 31st May 2016).

Fezzi, C. and Bateman, I.J. (2011) Structural agricultural land use modeling for spatial agro-environmental policy analysis, *Am.J.Agric.Econ.* 93 (4): 1168-1188, doi: 10.1093/ajae/aar037

Hampson, D., Crowther, J., Bateman, I.J., Kay, D., Posen, P., Stapleton, C., Wyer, M., Fezzi, C., Jones, P., Tzanopoulos, J., (2010) Predicting Microbial Pollution Concentrations in UK Rivers in Response to Land Use Change, *Water Res.* 44(16): 4748-4759. 10.1016/j.watres.2010.07.062

Ministry of Agriculture, Fisheries and Food (MAFF). 1986. *Agricultural Statistics in the United Kingdom*, HMSO, London.

Office of National Statistics. 1974–85. *Annual Abstract of Statistics*, London: HMSO.

Pudney, S. 1989. *Modelling individual choice: the econometrics of corners, kinks and holes*, Cambridge: Blackwell Publishers.

Tobin J. (1958) Estimation for relationships with limited dependent variables, *Econometrica,* 26(1): 24–36, DOI: 10.2307/1907382.

Yen S.T., Huang C.L. (2002) Cross-sectional estimation of U.S. demand for beef products: a censored system approach, *J. Agri. & Res. Econ.* 27(2): 320-334, http://purl.umn.edu/31124.