Agricultural Land-Use Change Modelling for Land-Use Planning in Thailand

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Abstract

This study compared the ability of different models to simulate possible land use changes at a crop specific level in two study areas within northern and north-eastern, Thailand: Mae Chan and Lam Mun Sub-watersheds.

Five models were examined: Dyna-CLUE, CA-Markov, Land Change Modeller (LCM), Multi-Criteria Evaluation (MCE) and Agent-based model (ABM). Modelling results were validated using observed data and three of the models were selected to produce simulations for 2025. These simulations were evaluated against further observed data and the expectations of local land use experts.

The results indicated variations in performance by models, between study areas and for different crops. The most promising models (CA-Markov, LCM and ABM) were selected for simulation. The CA-Markov performed well in validation but less so for simulation (changes occurred in restricted areas and were overly clustered). The validation was noticeably better in the second study area, which had different crops. Overall, the two models which performed best in simulations (i.e. trends matched observed data) were the LCM and the ABM, with the latter requiring appreciably greater effort to implement. The research found that it is possible to model agricultural land use change at the crop specific level using a range of different models, but certain land uses were more challenging to model. For instance, rice was better modelled than crops involved in rotations (sugarcane) or influenced by market or policy factors (pineapple and rubber).

While the insights here could be applied to land use modelling in other agricultural areas, it is difficult to specify a single 'best' model, as different modelling approaches may be suitable depending on the particular character of the study area and the objectives of the land planner. ABM shows great potential in areas where crop diversity is high and there is a desire to understand the motivations of farmers.

Table of contents

List of Figures

List of Tables

Acknowledgements

Someone told me that studying for a PhD is like walking into a cave. Before I start, I think the cave is a beautiful thing, easy to go into to see beautiful thing inside, and easy to go out, with a good memory. But it is not true. My PhD life is like I am stuck in the (dark) cave.
I try to go out by myself and someone has to help me get out of the cave, like the big news of the world in 2018, like the boys in the cave.

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Chapter 1 | Introduction

1.1 Background and Rationale

Food security is a global supply and demand issue associated with the relative balance of world population and the area of agricultural land. The Food and Agriculture Organization (FAO) reports that world population increased from 6.12 to 7.37 billion people between 2000 and 2015, while the agricultural area declined from 4.94 to 4.89 thousand-million hectares during the same time period (Food and Agriculture Organization, 2015). In other words, world population rose 11.8%, but agricultural area declined by 1.1%. If this trend in population and agricultural land continues, the world will face increasing food security issues in the future.

Population growth not only puts pressure on food supply but is also connected to energy and water demand. Beddington (2008) used the term 'perfect storm' to describe a situation where by 2030 the world will need 50% more food and energy and 30% more fresh water, while dealing with climate change. The Bonn Conference (2011) popularised the term 'Nexus' to describe the interactions between food, energy and water security, as well as emphasising the importance of evaluating interactions between these resources and identifying strategies for building synergies and improving governance.

The Food and Agriculture Organization (2014) and Gulati et al. (2013) provide further examples of the interdependencies between food, energy, and water resources, and how the availability of any one can determine the efficiency of production of the others. Food production, for example, demands energy and water. Energy is used for food production in fertilizers, irrigation, raising livestock and marine food, and is required throughout the value chain in processing distribution, storing, packing and transportation. Energy can also be required for water (e.g. pumping from borehole). As such, the volatility of energy markets can have a significant impact on food and energy availability which may influence food security (Popp et al., 2014; Fróna et al., 2019).

Other challenges are not simply a matter of increased population, but also stem from changes in lifestyles, particularly diet.

Dietary alteration can also have major implications for global food demand and freshwater resources (Fróna et al., 2019). The globalisation of food production systems provides some local farmers with access to larger-scale markets and investments. To increase global food production the most appropriate food crop should be encouraged at the local level (Charles et al, 2010).

Thus, if the pathways to improving food security are reduction in demand, increasing production and avoiding losses in the supply chain a good understanding of the food-energy-water nexus is needed in land management. (Ministry of Foreign Affairs of the Netherlands., 2012; Keating, et al., 2014).

Land management involves the integration of farming knowledge, technologies, and capital (Verheye, 2009) to maintain or increase agricultural production when faced with rapid urbanisation, migration, and land misuse (Bonn Conference, 2011).

Land use models can be used to simulate changes in agricultural land use, based on past trends or knowledge of drivers or pressures. They can also be used to understand environmental contributors to change. Modelling can also provide a means to identify and address land use problems which may occur in the future (Veldkamp and Lambin, 2001).

Land use models contain different functions, which are possibly useful and appropriate depending on the available input data and the objective of the study (Mas et al., 2014). Models typically compare the multiple land use models in different land use categories to predict and simulate land use change.

Land use modelers have many choices of application and software packages. In recent years, many have tried to include physical, ecological and socio-economical concerns within the land use simulation, for example, Shutidamrong (2004) and Walsh et al. (2009). These more complex models, however, require greater skill, data, and time to construct. Land use models contain different functions, the appropriateness of which depends on the available input data and the objective of the study (Mas et al., 2014). Thus, the examination of which is the most suitable and effective model for land use planning needs to consider a range of issues.

Land use change models can be evaluated by an accuracy assessment (e.g. comparison of modelled output to observed land use for a baseline year or years). This method can help to ensure that an appropriate model is selected for simulation of the future land use. Confidence in the selection of an appropriate model can be improved if model performance is verified under different conditions. Model evaluation in multiple study areas can also help to understand the relationship between the characteristics of the study area and performance (Lenormard et al., 2015; Sun and Robinson, 2018). It is suggested that local variations (e.g. environmental and socio-economic factors) might help to explain differences in cropping and land use allocation (Rounsevell et al, 2003). This may also reveal geographical differences in model performance i.e. some areas may be easier to model than others.

Study Area

Thailand is a country in South-East Asia, which is important for global food security. It is a surplus producer at the national level and is a net exporter of agricultural and food products. Important internationally tradeable crops grown are Rice, Maize, Sugarcane, and Cassava for example. Thailand has a high potential to increase agricultural production for the world market, e.g. there is a national agenda to develop agro-industries and the country is one of the top five rice exporters in the world (Thailand Board of Investment, 2012; 2015; International Rice Research Institute, 2015; Isvilanonda and Bunyasiri, 2009). In 2014, national rice production was 28 million tons, 9 million tons of which was exported. However, Thailand is facing production challenges because suitable land for agriculture is being lost to non-agricultural uses (due to socio-economic factors, migration or increasing population).

1.2 Research objectives and questions

This thesis will compare the ability of different types of land use models to simulate possible land use changes. The research aims are to compare the ability of different types of land use model to predict and simulate possible land use changes at the crop specific level, and to investigate past cropping and future production potential in two study areas of Thailand. Two study areas were chosen to encompass a diversity of environmental characteristics and land uses. These research aims lead to four research questions:

1. How is land currently being used in the study areas and how has use changed in recent years?

2. Are some types of model better than others for simulating (certain types of) land use change?

3. What are the possible simulated changes in land use for 2025?

4. How well did the simulations perform, and which were the most robust simulations?

1.3 Outline of the thesis structure

This thesis is organised in seven separate chapters. This chapter (Chapter 1) provides a study background and rationale, and a statement of research aims. This is followed by Chapter 2, where a review of land use change models is presented leading to the selection of land use change models for comparison.

Detail of the overall research design and data collection is given in Chapter 3. The significant characteristics of the study areas: Mae Chan Sub-watershed (MCSW) in Chiang Rai province (Northern region of Thailand) and Lam Mun Sub-watershed (LMSW) in Buriram and Surin province (North-eastern region of Thailand) are also introduced.

Land use model set up and calibration is discussed within Chapter 4. The models are Dyna-CLUE, three modules within IDRISI TerrSet (CA-Markov, Multi-Criteria Evaluation (MCE), Land Change Modeller (LCM)) and an Agent-Based Model (ABM).

Chapter 5 presents and compares the results from the validation of the various models which were introduced in Chapter 4. Error matrices are constructed to compare the simulated results with observed data for 2015/16. The accuracy assessment includes several measures of accuracy (overall accuracy, producers' accuracy, and users' accuracy).

Simulation of land use in 2025 from three different models in presented in Chapter 6. A visual analysis of the simulation outputs is performed, along with comparison of observed data for an interim year (2018/19) and with the expectations of local land use experts.

This is followed by the study conclusions in Chapter 7. These include the key empirical findings from the modelling, as well as the suitability and limitations of the different methods. It includes an assessment of which approaches to modelling are most useful for land use planning in Thailand. The chapter concludes with some recommendations for further research.

Chapter 2 | Literature Review

Land cover is defined by the Food and Agricultural Organization of the United Nations as “the observed (bio) physical layers on the surface of the earth” and land use is characterised “by the arrangements, activities and inputs people undertake in a certain land cover type to produce, change or maintain it” (FAO, 2005. p1). Lambin (2004) emphasises that land cover pertains to an inherent part of the earths’ land surface and associated characteristics such as topography, soil, groundwater, the animal life and plants, and manmade structures. While changes in the (bio) physical attributes of land (i.e. cover) are relatively easy to monitor, classify and map using satellite data, for example, land use change is inherently more complicated due to the additional human dimension. A single land cover can have multiple land uses in a one-to-many relationship.

While land is a limited resource, global population increase brings a rising demand for food, energy, and water (Bonn Conference, 2011, McKenzie and Williams, 2015; Ruiter et al., 2017). Land is the foundation for vegetation and fresh water thus food security is necessarily based on good management of this resource (Bonn Conference, 2011; McKenzie and Williams, 2015; Fitton et al., 2019). For agricultural area prediction, land use change models are necessary tools to help deal with problems of land use that may arise in the future.

This chapter discusses some of the fundamental concepts of land use modelling, reviews some of the available frameworks, and looks at previous studies to inform the methodology and the model selection for this study.

A review of the causes and consequences of land use change is presented in Section 2.1. Section 2.2 introduces the basic concepts of land use change modelling and the different types of model which are available. Section 2.3 discusses the criteria for land use model selection and some examples of previous land use change studies in Thailand. The chapter concludes with a discussion of the initial selection of land use models for this research.

2.1 Land use change causes and consequences

In the study of land use, there are multiple ways to understand and analyse land use change, and a number of research frameworks exist to organise these ideas. In order to understand the causes and consequences of land use change, it is important to know how changes occur and how environmental and socio-economic conditions influences the changes and potential feedbacks (United States Environmental Protection Agency, 2012; Pullanikkatil et al., 2016; Khunnanake et al., 2018). The DPSIR (Drivers, Pressures, State, Impact, and Responses) framework is one such example.

The DPSIR Framework, developed by the European Environment Agency (EEA) in 1999, is a formal analysis that explains land use change as the relationship between the environment and human agents. The objective of the DPSIR framework is to analyse the cause-and-effect relationships between the interacting factors in environmental and socio-economic system. The framework consists of five components: ***Drivers*** (D), ***Pressures*** (P), ***State*** (S), ***Impact*** (I), and ***Responses*** (R) (Figure 2.1). This system perspective on environmental change starts from the identification of ***Drivers***. The relevant drivers for land use change include underlying causes such as economic conditions, technological change, political conditions, or population growth, which frame the future conditions. ***Drivers*** can be the human needs and activities that impinge on the environment exerting ***Pressure*** (which is stress caused by driving forces such as changes in demand, expansion of agricultural land, or urbanisation). The relevant pressures for land use change are direct forces, which cause changes in the land use categories and patterns. These forces then influence the ***State*** (the current condition or spatial condition) of the land use or the environment (at any one time). The bio-physical state of the land results from its socio-economic setting and the various pressures on the land. The state of the land use refers to the various categories of land use, which are identified, and the quantity and distribution of the land uses. The land is also the location for the consequences of land use change (such as soil erosion and rising land price). Changes in the state lead to ***Impacts*** on environmental quality and functions (i.e. changes in the environment that may influence human-beings in some way), in other words, impacts are effects on the variable factors (e.g. water availability, agricultural area, forest area) and can affect quality of life and sustainable development. Impacts might include a decrease in productive land, loss of soil quality and increased/decreased population density. Impacts also may lead to social and political ***Responses***. These refer to the human reactions to the changing situation, which may evoke societal and political reactions – such as setting indicators or priorities. The response can address the pressure to improve or maintain the state (Figure 2.1). In terms of land use responses, these include specific policies and legal instruments that relate to land use, such as land use zoning, or restrictions on use (e.g. on deforestation).

These social and political responses influence the system at various points (by changing the drivers, by creating or relieving pressure on the environment). These responses in their turn can influence the state of the environment.

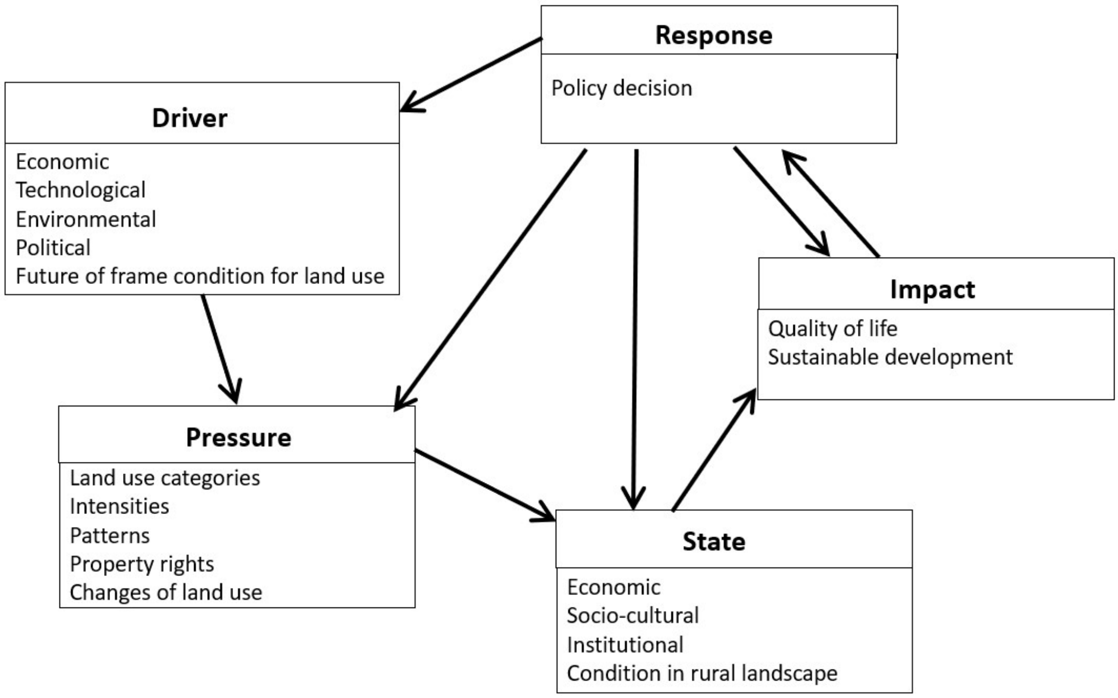


Figure 2.1 The DPSIR framework (EEA, 1999) and adapted for analysis of land use change (Helming et al., 2012)

It is this interaction between physical changes in the environment and the human responses which creates a dynamic system. It also emphasises that land use change occurs within a complex system, which is not straightforward to model.

The DPSIR framework can be used as a tool to help provide land use planners or decision makers with an understanding of land use change (Helming et al., 2012; Pullanikkatil et al., 2016; Gedefaw et al., 2020).

2.1.1 The causes of land use change

Driving forces are the factors that increase or decrease the probability of change (Turner et al., 1995; Veldkamp and Lambin, 2001; Zondag and Borsboom, 2009; Sonter, 2014; Robinson et al., 2018). Understanding and assessing the driving forces (or causes) of land-use change helps explain the resulting pressures and changing state of the environment. The subsequent impacts can be described as consequences of land use change. Assessing which driving forces are important is an essential requirement for simulating the future land dynamic and supporting the development of land management strategies (EEA, 1999; Hersperger et al., 2010).

These driving forces (***Drivers***) can be grouped into five categories which are 1) economic factors, 2) demographic factors, 3) policy and institutional factors, 4) technological evolution factors and 5) cultural factors (Geist and Lambin, 2002; United States Environmental Protection Agency, 2012). Most of these five groups can be further disaggregated. Firstly, in the case of economic factors these can be identified as market growth and commercialisation (growth of demand for consumers goods and services), urbanisation and industrialisation, and specific economic structures (poverty, economic crisis conditions and indebtedness). Secondly, in terms of demographic factors, these can be identified as population growth, population density, and life cycle features. Thirdly, policy and institutional factors can be differentiated as formal policies (on economic development, credits), informal policies or policy climate (corruption, mismanagement) and property rights (land tenure). Fourthly, technological evolution factors can be described as agro-technical change (land use intensification/extensification, agricultural evolution), or another production factor (labour, capital, land scarcity). Lastly, in terms of cultural factors, these can be identified as public attitudes/values/beliefs, individual and household behaviour (Geist and Lambin, 2002; Vliet et al., 2016; Kleemann et al., 2017). Social trigger events (war, health crisis, government policy failures) can be additional underlying causes of land use change (Geist and Lambin, 2002; United States Environmental Protection Agency, 2012).

The proximate causes of land use change (or ***Pressures*** of DPSIR) are human activities and actions that directly affect the environment in order to fulfil societal needs from the land. The actions taken by individuals are constrained by the fundamental biophysical factors (environmental heterogeneity). Proximate causes can be grouped into three categories which are 1) the expansion of agricultural land, 2) wood or timber extraction by harvesting of yield and 3) infrastructure expansion, (Geist and Lambin, 2002; United States Environmental Protection Agency, 2012). Agricultural expansion can take a number of different forms depending on the specific type of agricultural expansion for example: shifting cultivation, permanent cultivation, cattle ranching or pasture creation. Wood or timber extraction includes activities, such as commercial wood extraction (logging), fuelwood extraction, pole wood extraction (wood for house construction) and charcoal production. In terms of infrastructure extension, identified activities include new transport infrastructure (road network development), market infrastructure, public services (water supply, electrical, etc), settlement expansion and private enterprise infrastructure (mining, oil exploration) (Geist and Lambin, 2002; Qasim et al., 2013; United States Environmental Protection Agency, 2012; Wubie et al., 2016). Moreover, other factors such as the land characteristics (soil quality, topography, land size and vegetation density) and biophysical triggers (soil compaction, drought and floods) add to the proximate causes because some of these exert a direct impact upon the land use change (Geist and Lambin, 2002; Pullanikkatil et al., 2016).

Often, it is difficult or impossible to attribute land use changes to a single cause, as multiple drivers, with both proximate and underlying causes, may interact and be spatially and temporally variable.

2.1.2 The consequences of land use change

Rapid population growth, and increasing demand for agricultural products, is one of the many underlying causes of land use change, i.e. land allocation to agriculture is being driven by the need to provide food, fibre and energy to the world's population (McKenzie and Williams, 2015).

The consequences of land use change (or the ***Impacts*** in the DPSIR framework) can be biophysical or socio-economic in nature and can be viewed either positively or negatively. Impacts can relate to the quality of life or wellbeing (e.g. health, living standard).

The overall area of agricultural land in the world has expanded, and this change has been accompanied by substantial increases in energy, water, and fertiliser consumption. However, agricultural practices have feedbacks for other ecosystem services and goods that could potentially have consequences for food production, forest resources, freshwater resources, and regional climate and air quality (Foley et al., 2005; Intergovernmental Sciences-Policy Platform on Biodiversity and Ecosystem Services, 2019).

Increased food production has caused extensive environmental damage. For instance, changing land use practices have made it possible for grain harvests to increase due to mechanisation, irrigation, high yield cultivars, and the application of chemical fertilisers and pesticides (Foley et al., 2005; Rega et al., 2019). Some agricultural land may experience degradation in terms of soil erosion, a reduction in fertility, or over-grazing. Irrigation can lead to salinization of the soil in some cases, leading to a loss of arable land around the world. Increasing the use of fertilisers has led to a deterioration in the quality of water. In addition, some habitat losses may affect agricultural production by reducing pollination (Foley et al., 2005; Rega et al., 2019; Bennett et al., 2020).

As well as the process of land use change there have also been changes in farming production technology. Modern high yield varieties allow farmers to produce the same crop yields with less resource input in terms of labour and land (Forbord et al., 2014). Forbord et al. (2014) found that greater capital resources were being invested in the land per hectare in the purchase of seeds and fertilisers, as well as the cost of machinery for example. The implication is that further agricultural expansion (causing deforestation) is unnecessary if yields can be improved. This type of process also has socio-economic effects as farmers have to have access to capital for example.

Wu (2008) states that land can be seen as a resource and land use change is necessary for economic development. The author also notes, however, that land use change has costs, for example conversion of farmland and forests to urban development reduces the amount of land available for food production (Wu, 2008).

Changing land from forest to agricultural use, or poor agricultural practices, can lead to soil erosion or landslides that influence water quality in rivers by changing the deposition of sediments, for example. Artificial drainage and terracing have also been identified with changes in flooding (Glade, 2003; Rogger, 2017; Razali, 2018). Land use change can have a strong effect on soil nutrient levels, causing nutrients and organic matter in the soil to decrease (Mander et al., 2000; Weller et al., 2003).

Depending on freshwater resources, the expansion of the agricultural area may disrupt the balance of surface water and contribute to evapotranspiration, runoff, and ground water flow. Surface runoff and the discharge of rivers increases when the forest is cleared. Water demand associated with land use practices or irrigation directly affects the supply of freshwater through water withdrawals and diversions. Water quality is often degraded by intensive agricultural land use increasing erosion and sediment loads and releasing nutrients and agricultural chemicals to groundwater, streams, and rivers. The resulting degradation of inland and coastal waters impairs water quality, causes oxygen depletion, and kills fish, and increases the toxicity of the species (Foley et al., 2005; Global Water Partnership, 2014; Hutchins et al., 2018).

Expansion of the area of agriculture can lead to an increase in demand for water if the crops are irrigated. Surface water and ground water are the main sources for irrigation, but the impact on ground water is particularly high (Ghazavi, 2016; Aghsaei et al., 2020). Agriculture has a complex relationship with the water cycle. Agricultural land can discharge water though evapotranspiration as well as facilitating recharge in an irrigated agricultural system, leading to a change in the flow direction from upward (discharge) to downward (recharge) (Scanlon et al., 2005).

Runoff from agricultural land causes water pollution while changes in land use such as the change from agricultural land to urban can increase runoff, increase nutrient loss in runoff and increase heavy mental concentrations in the runoff from hard surfaces. Irrigation of the agricultural area has changed the water cycle and is reducing groundwater levels in many regions. Deforestation (for example) leads to an increase in the farming area but can increase the possibility of soil erosion, landslides and flooding, while land use management has a direct impact on features such as soil, nutrients and vegetation (e.g. crops remove nutrients from the soil) (Bhaduri et al., 2000; Tang et al., 2005; Chotpantarat and Boonkaewwan, 2018). For example, at regional and local scales, Camara et al. (2019) showed that agricultural and some forest-activities affected water quality though their correlation with physical and chemical indicators of water quality.

At a global scale, land use change can have a major impact on climate due to changes in temperate and boreal vegetation. Land use change activities also change air quality by altering emissions and changing the atmospheric conditions. For example, biomass burning, vehicle emissions and other air pollution are often particular results of changes in land use (Foley et al., 2005; European Environmental Agency, 2012).

Land use change has potentially severe socio-economic consequences. The transformation of agricultural land to urban or forest for example decreases the amount of available land for food production, while the oversupply of certain agricultural commodities in the world market drives prices (and income) downwards (Wu, 2008). Another consequence of agricultural land use change can be increasing risk to household income (Asadi et al., 2015; Pullanikkatil et al., 2016).

The ***Response*** of the DPSIR framework comes after the ***impact*** of land use change, in other words, this part of the framework concerns the policy decisions or response that society (groups or individuals) and governments can make to land use change. This may directly or indirectly affect any other part of the framework (United States Environmental Protection Agency, 2012; Helming et al., 2012).

Responses can be varied. They can seek to influence ***Drivers***, ***Pressures*** or ***State*** through policy initiatives such as legislation, restrictions or guidelines that directly or indirectly influence another part of the framework. Responses may affect the use of the land by influencing agricultural management practice for example. To put it more simply, the farmers cannot apply pesticides or other chemicals at certain times or only undertake some operations at a particular time of year. This would influence the pressures on – and state of – the environment and may influence the choice of crop. ***Responses*** which influence ***Drivers*** can also be policy responses to do with taxation which might provide financial incentives. Tax can also add expense, which would discourage people from doing certain activities. ***Responses*** related to ***Pressure*** might be specific regulations that relate to specific locations and times. The response can also address very specific ***Pressures***. The ***Responses*** may seek to control ***Pressures*** through regulations which limit human activities or are designed to modify human behaviour such as land use zoning or designating protected areas. In addition, ***Responses*** may directly affect the ***State*** of the environment (e.g. specifying that forest is not removed). ***Impact***-based ***Responses*** may be designed to measure or compensate for socio-economic impacts on human beings, e.g. requiring the monitoring of water quality (United States Environmental Protection Agency, 2012; Helming et al., 2012; Pullanikkatil et al., 2016).

2.2 Land use (change) models

By analysing the relationships between land use driving forces and the changing state of the environment, land use modelling can calculate and compute the magnitude and location of the changing land uses (Verburg et al., 2004; Heistermann et al., 2006; Robinson et al., 2018). Land use change models can be used to evaluate the link between a number of different elements of the DPSIR framework. Models often sit between ***Drivers***/***Pressures*** and ***State***, that is, they try to model the influence of various ***Drivers*** and ***Pressures*** on the ***State*** of the environment. For example, an Agent Based Model (ABM) can incorporate the decision making of human agents into the model, and this decision making is likely to take into account the ***Drivers*** of land use change and to produce ***Pressures***.

A land use change model can be defined as a tool to support the analysis of changes in land use (Veldkamp and Lambin, 2001; Verburg et al., 2004; Koomen and Stillwell, 2007). The purpose of a such a model should be to enhance understanding of the land use system, explain the behaviour of the system under changing conditions and/or to apply scenario analysis to assist strategic planning (Koomen and Stillwell, 2007; United Nations Environmental Programme, 2016). Land use modelling can be used to support observation, assessment, evaluation, and decision making on land use management (Brown et al., 2013). A distinction can be made between explanation and prediction. The aim of explanation is to identify which land use decision theory better explains the observed land use outcomes. The purpose of prediction is to produce an estimation of the amount of land use/or spatial allocation of land use under some specified situation in the future (Paegelow and Olmedo, 2008; Holzhauer et al., 2019).

Land use planning models can be implemented in various ways and at different spatial scales (depending on the project purpose) (Briassoulis, 2000; Lambin, 2004). Modelling objectives, and the time-period of evaluation, will be selected by the land use modellers and/or planner.

A land user refers to someone who is making decisions about land use by weighing the values of environmental, economic, and social factors in order to select the appropriate land management. Land use plans can help with problem identification, the determination of alternative resolution, the choice of the best alternative and the plan arrangement and the plan of action. (FAO, 1993; Turner et al., 1995; Amler et al., 1999). These plans can be useful as a guide for land use planners and land use managers.

There are two main perspectives in the discussion on land use change models. One perspective focuses on broad categories of land use change models distinguishing four main types (see Section 2.2.1), and the other perspective looks at the conceptualisation of the land use models in terms of six main features (such as ability to model neighbourhood effects and incorporation of feedback loops, see Section 2.2.2).

These perspectives are useful for framing the discussion of model selection (to follow in Section 2.3).

2.2.1 Categorisation of land use change models

Land use models have been categorised by different researchers in a variety of ways. Four types of model were identified by Lambin et al. (2000) and Lambin et al. (2004) which were; Empirical-statistical models, Stochastic models, Optimisation models, and Dynamic (process-based) models. Integrated modelling approaches combine elements of more than one type. Other reviews of modelling included those by Heistermann et al. (2006), Koomen and Stillwell (2004) and (Lantman et al., 2011). Heistermann et al. (2006) compared 18 modelling approaches and applications, and a distinction was made between geographic models, which focus on the development of spatial patterns of land use types, and economic models, which focus on drivers of land use change from the demand side (a third class of *integrated* models combined both geographical and economic aspects). Koomen and Stillwell (2004) classified models based on five attributes which were 1) static or dynamic, 2) transformation or allocation, 3) deterministic/probabilistic, 4) sector-specific and integrated, and 5) zones and grids. Lantman et al. (2011) found that simulation models were always based on at least one of the following principles 1) continuation of historical development 2) suitability of land (in monetary or other units) 3) result of neighbourhood interaction, and 4) result of actor interaction.

While previous reviews of the land use modelling literature present a variety of classification schemes, the framing by Lambin et al. (2000) and Lambin et al. (2004) is still mentioned and used in contemporary studies (e.g. Otuoze et al., 2020) and will therefore be adopted as the main framework for review in this case.

Empirical-statistical models: the empirical model aims to identify the cause(s) of land use transition using multivariate analysis of the possible contributions to land use change (the drivers). The resultant statistical model projects the pattern of land use into the future. Thus empirical-statistical models are used to explain the relationship between land use and driving forces and to simulate the future by extrapolating forward from past trends. Empirical-statistical models can also combine GIS with multivariate statistical methods to analyse the location of land use change that relates to a map in GIS. Examples of this type of model are Dyna-CLUE (Dynamic Conversion of Land Use and its Effects) (Verburg et al., 2009) and Dinamico EGO (Britaldo et al., 2009).

Dyna-CLUE, for example, uses a statistical analysis to reveal and quantify the relation between the different land use categories and the influencing factors. Binary logistic regression is used where the dependent variable is dichotomous, and the independent variables are categorical or continuous. The model structure supports land use change analysis in relation to biophysical and socio-economic driving forces. Moreover, Dyna-CLUE is a specifically developed model for land use change analysis in small regions like provinces or watershed boundaries, at a fine spatial resolution (Verburg, 2002; Verburg, 2004; Verburg and Overmars, 2009; Lantman et al., 2013; Tizora et al., 2018).

The strength of the statistical approach is that these models can identify the influence of driving forces that can be applied to the spatial area to determine the outcome of land use change. But such models can only explain the pattern of observed land changes and are less suitable for application to long term simulation analysis (over 20 years) (Lambin, 2004; Verburg et al., 2004; Dang and Kawasaki, 2016).

Stochastic models: describe processes that move in step though a sequence of different states. The states of the system are defined as the amount of land in the different land use categories at any one time. Random variation in one or more input(s) is used to determine transition probability (the probability of changing from one category to another during a certain time interval). Examples of stochastic models are Markov chain (Thornton and Jones, 1998), Cellular Automata (CA) models such as SLEUTH (Slope, Land use, Exclusion, Urban, Transportation, Hill-shading) (Clarke, 2008), and CA-Markov models (a result of combining Markov chains and CA), CA-Markov associated with Multi-criteria Evaluation (MCE), CA-Markov with Land Change Modeller (LCM) (Clark et al., 2006), and GEOMOD2 (Pontius et al., 2001).

A well-known example of a stochastic model is CA-Markov (Agarwal et al., 2002; Lantman et al., 2013; Tajbakhsh et al., 2018). This type of change prediction is based on the continuation of historical development trends. The Markov chain calculates the land use change trend from a pair of land use maps, the output of which is a transition matrix. The matrix shows the land use transition probabilities based on maps from two different dates. However, as noted by several authors, an important caveat for use is that the Markov chain has no specific spatially referenced output (Pontius et al, 2001; Lantman et al., 2013; Eastman, 2016). CA-Markov combines the Markov chain with a Cellular Automata, which allows the output to be spatially referred.

Cellular Automata (CA) can also be used for land use prediction. CA consists of four elements; a cell or a grid, the state of the cells, a neighbourhood cell arrangement, and transition rule for each cell and the time step. The cell is the basic unit of the model while the state is the current value of the cell. The state represents a series of data values that each cell can possess at any one specific time point. The other cells, within a certain distance of the central cell, are defined as the neighbourhood. The transition rule is a function for determining the state of the cells during each time step. In other words, the state of a cell is based on the condition in the surrounding cells and a set of transition rules. Moreover, CA can consider interactions with neighbourhood cells and can also be geo-referenced (Koomen and Stillwell, 2004; Lantman et al., 2013; Eastman, 2016).

CA-Markov combines a Markov Chain with Cellular Automata. This type of model has been extensively used in modelling and predicting land use change. The CA-Markov model uses the output of Markov chain analysis, principally the transition area data file, and applies a nearness filter to simulate the development of other land use types (Subedi et al., 2013; Eastman, 2016; Tajbakhsh et al., 2018).

A particular strength of the CA-Markov approach is that it can benefit from both CA and Markov chain techniques. Another benefit is that the map simulation from this model can be multi-categorical. Moreover, the CA-Markov model in IDRISI, Land Change Modeller and Multi-criteria Evaluation (MCE) in IDRISI, can be used to create transition probabilities and the metric transition by cross-tabulation from two different images and times (Agarwal et al., 2002; Jamal, 2011; Subedi et al., 2013; Hamad et al., 2018).

Optimisation models: are originally from the field of economics and are mostly applied to economic aspects (such as profitability). These models investigate the demand and supply of the land market (and the effects on agricultural intensity). Optimisation models can be used for decision-making based on linear programming or an equilibrium model. An example of liner programming is the Robust Optimisation model (Bertsimas et al., 2010). In an equilibrium model the model presents land allocation, where the main mechanism is to equate model demand and supply under exogenously defined constraints. The optimisation models recently developed by economists integrate spatial heterogeneity and broaden the objective function of actors from profit maximisation. An advantage of the optimisation model is that it can consistently address demand and supply via a process mechanism where the main objective is benefit maximisation (such as maximising yields or income). Examples of optimisation models are Computable General Equilibrium (CGEs), Partial Equilibrium Models (PEs) (Briassoulis, 2000; Lambin, 2004) and the IMPRESSIONS Integrated Assessment Platform (Harrison et al., 2015, 2019).

Dynamic (process-based) models: simulate changing temporal and spatial land use patterns based on an understanding of the interaction between the driving factors and land use change processes. Process-based model can be parameterised based on decision-making (from local observation). Examples of this type of model are the Sahelian Land Use model or SALU (Stephenne and Lambin, 2001) and Agent-based models (ABM). The SALU model has been used to simulate spatially explicit land use using a sequences of agricultural land use changes for the Sahel zone (United Nations Environmental Programme, 2016).

An Agent-based model examines the potential causes of change at the level of the individual agent's behaviour in response to the changing and the independent dynamics of various factors. The ABM simulates the decision making of users and integrates their knowledge and abilities with biophysical and socio-economic data to evaluate land use decision-making (Berger et al., 2002; Goodchild, 2005; Matthew et al., 2007; Brown et al., 2021). An advantage of the dynamic models is that the agents' behaviour can be described within the model and has the capacity to inform simulations (and future land use plans).

Integrated modelling approaches: also described as hybrid models are based on combining elements of the different land use modelling techniques described above. The integrated models can be combined in ways which are most appropriate in answering the specific questions of land use change (Lambin et al., 2000; Lambin et al., 2004). An example of an integrated model is the Integrated Model to Assess the Global Environment (IMAGE) which is a combination of optimisation and process-based models. Appling the integrated approach can potentially offer a useful understanding of a complex land use system. IMAGE is used for enhanced understanding of the consequences of the intensification processes. This model framework has been used for understanding how long-term global environmental changes are driven by human activities (such as population growth) (Stehfest et al., 2014).

2.2.2 Concepts of land use modelling

Verburg et al. (2004) define land use change modelling concepts based on six features: 1) level of analysis, 2) cross-scale dynamics, 3) temporal dynamics, 4) driving forces, 5) spatial interaction and neighbourhood effects, and 6) level of integration. This framing of approaches to modelling is useful to aid model description and selection and is described in more detail below.

Level of analysis: two levels of analysis can be distinguished. Social sciences research has mostly studied individual behaviour, which is the micro-level, while the natural sciences have mostly applied spatial technologies (remote sensing and Geographic Information System, GIS) to study macro-level trends. Macro-level approaches are perhaps more common for studying land use change, but both types of model have been applied in previous studies. The concept of micro-level relates to changes in the land use pattern that are based on individuals and the upscaling of individual behaviour. Well-known micro-level land use models are the Land Use Dynamic Simulator (LUDAS) and Agent-based models (ABM), which are spatially explicit, integrating the biophysical and socio-economic modelling approaches (Le et al., 2008; Le et al., 2010).

Macro-level land use change models are based on an analysis of the spatial structure of land use and are not bound to the behaviour of individual agents. Well-known macro-level land use models are the Conversion of Land Use and its Effect or CLUE (Verburg and Veldkamp, 2004) and GEOMOD2 (Pontius et al., 2001).

Cross-scale dynamics: Cross-scale dynamics are concerned with the interactions of the spatial, temporal, quantitative, or analytical dimensions used by scientists to measure and investigate objects and processes (Gibson et al., 2018). Land use is a function of multiple processes operating at a range of scales (Turner et al., 1995; Agarwal et al., 2002). Land use in any given area will be influenced by a combination of environmental, economic, and social conditions (e.g. supply of labour) at the regional level, national policy, and global economic trends. For example, while demand for sugarcane acts as a global driver, land use planners must also make decisions at a local scale (e.g. considering variations in factors such as soil types) (Verburg et al, 2006; Olmedo et al, 2015). To fully comprehend spatial scale, concepts such as resolution and extent are commonly used, especially in land use modelling. The resolution refers to the precise dimension (or size) of the cells in a raster grid system (e.g. 50×50m cells) or the scale of the vector layers (e.g. 1:50000).

The extent refers to the size of the study area (local, regional, or national). Temporal scales can be very long-term change over timescales of decades, or they can be much shorter timescales, such as those related to an extreme weather event for example (further details below).

Temporal dynamics: The temporal resolution refers to how frequently the change is being measured or simulated, while temporal extent describes the length of the study period. Time step and duration are key measures of temporal dynamics and are an analogue to spatial resolution and extent (Agarwal et al., 2002; Peuquet, 2005; Degbelo and Kuhn, 2018). The connection of the temporal dimension to land use change is established in the validation stage. Model validation can be achieved through the comparison of model simulation outputs for the historical land use data with the actual observed land use data. It is important to establish the temporal dynamics of the models (to understand the rate of change and the likelihood of change in any given year), and to use the initial land use as a criterion for the subsequent change (e.g. CA-Markov). For example, Behera et al (2012), Olmedo et al (2015) and Khan et al (2016) studied the temporal dynamics of land use changes by considering the quantity of change within a certain interval of time.

Driving forces: the selection of driving forces is mostly based on generalisations from theoretical and behavioural assumptions. Quantification of relationships between land use change and driving forces can be attempted using theories and empirical relationships (for example, economic models which are mostly based on demand and supply), statistical techniques, and the use of expert knowledge. For example, Dyna-CLUE, (introduced in Section 2.2.1) can identify the influences of various driving forces using logistic regression.

Spatial interaction and neighbourhood effects: The spatial interaction between land use categories can cause spatially autocorrelated land use patterns. Autocorrelation is generally seen in the clustered distribution of land use categories (for example, expansion in the area of urban land is often seen next to existing settlements). A common method to introduce spatial interaction to the model is Cellular Automata (Section 2.2.1) which has a strong neighbourhood effect built into the model.

Level of integration: land use systems are the integration of interdependent parts and the interlinked interaction that make it possible to identify the causes and effects of land use change. Interactions between the parts might take the form of feedback loops to distinguish causes and effects (e.g. the feedback loops of the DPSIR framework in Figure 2.1). Various factors such as demographics or transportation have the potential to influence the land use system. These are described as sub-systems and can be modelled and analysed separately or as part of the main model. Models may or may not attempt to integrate these factors into the main land use model. Examples of integrated models include the International Institute for Applied System Analysis IIASA-LUC model (Fischer and Sun, 2001) and Land Use, Land-use Change and Forestry Dynamic (LULUCF) (Michetti, 2012).

2.3 Land use model selection

2.3.1 Criteria for model selection

As discussed above, land use change models can be grouped according to a variety of modelling practices and conceptual backgrounds. The suitability of land use models depends on the purpose, the spatial and temporal analysis level, the dynamics of the model, the conceptual nature of the model, the data aggregation and data used, the technical or specific aspects of the model, and possible real-world application.

Table 2.1 formalises the criteria for model selection under seven headings which are; relevancy, applications and technical, data requirements, linkage potential, transferability, output reliability, and model access and difficulty. These are synthesised from a larger list of criteria proposed by the United States Environmental Protection Agency (United States Environmental Protection Agency, 2000; Gaunt and Jackson, 2003).

Table 2.1 Criteria, features and questions addressed relevant to model suitability (after United States Environmental Protection Agency, 2000; Gaunt and Jackson, 2003)

Criteria	**Features to be evaluated**	**Specific questions to be addressed**
Relevancy	- Model and forecast outcome for scenarios - The type of land use change which will be evaluated and the issues to be addressed by the study	- Do the model outputs relate to what the user requires? - Does the model provide information on what needs to change? - Which land use change will be evaluated? - Has the model been applied in similar studies before?
Applications and Technical	- Hardware and software - Budget - Documentation and the user's technical expertise	- Is the model (software) compatible with computer requirements (hardware)? - What is the cost of the software? - How long does the model take to implement? - Does the model provide sufficient support for the implementation of the model? - Do the models require technical expertise to operate the model and interpret the outputs?
Data requirements	- The necessary data (i.e. satellite imagery, aerial photography)- Scale of the data - The user's ability to collect data Spatial and temporal aspects	- What is the data requirement? - What are the spatial and temporal resolutions?
Linkage potential	- The ability of the model tool to join with other software (e.g. GIS)	- Can the model link to other models/software or connect to other disciplines?
Transferability	-The ability to change or modify location/platform -Site specific information (e.g. land use categories, available data and resources, time period and special extension)	- Can the model be applied to locations/platforms other than the one for which it was developed?
Output reliability	- Accuracy - Reliability - 'Goodness-of-fit' results when compared against the scenario	- What is the accuracy of the model? - How is the model to be widely used in real-world situations?
Model access and difficulty	- Process - Changing variables (i.e. land use, transportation) - Map, graph, and table (interpretation of the output)	- Can the model accommodate changing variables? - What is the ability of model evaluation? - Can the model be approached and interpreted? - Is the model easy to research/process?

The first criteria for model selection in Table 2.1 is relevancy. It is necessary to consider whether the model provides the appropriate information and evaluation for the questions under investigation. After evaluating model relevancy, modellers have to consider model applications and technical aspects (e.g. the required hardware, software, and available budget), data requirements, linkage potential, transferability, output reliability and model access and difficulty. Output reliability can only be determined once the models have been run. There is no reliability test for the simulation process, but the validation process can sometimes provide an indication of the plausibility of the output.

In order to make a preliminary assessment of relevancy for potential models, the next subsection reviews previous modelling of land use change in Thailand.

2.3.2 Previous modelling of land use change in Thailand

Reviewing previous studies can indicate which models are most commonly used, and which have been used less often. Where models are commonly used this would tend to suggest that other researchers considered these models suitable choices. Use in previous studies can indicate the *relevancy* of a particular model (which is the first criteria for model selection). On the other hand, the review of existing literature might reveal research gaps where particular types of model have not been applied or have rarely been applied in the context of Thailand. This research could help to establish the relevancy of particular types of model in the context of agricultural land use change in Thailand, and some of the conclusions could have broader implications.

Thailand is an interesting country to study because it has a large and diverse agricultural area. Agricultural products are important in generating export earnings. Thailand is also important for world food security as the kingdom has a large surplus in many crops such as Rice, Cassava, and Sugarcane. Thailand has 5.91 million agricultural holding, and a large proportion of the population derive at least part of their income from farming (Agricultural Census, (National Statistical Office, 2012)). As with other nations the country is experiencing change as new infrastructure is developed in rural areas. Other changes which can be observed in the country include industrialisation and urbanisation. These processes can create pressures on the land, while the economic and social changes also potentially influence the use of the land. Policy makers are keen to understand the likely changes in land use and their implications, and to ensure that land is used wisely.

Example applications of empirical-statistical models:

Dyna-CLUE is a model that has frequently been chosen to study land use change in Thailand. For example, Trisurat et al. (2010), Akber and Shrestha (2015), Shrestha, et al. (2018), Sakayarote and Shrestra (2019) and Shrestha et al. (2020) used Dyna-CLUE to determine the spatial distribution of land use change and to simulate land use change across different regions of Thailand. The sizes of the study areas in the previous studies were relatively large, commonly regional level studies, with a fairly coarse resolution. For example, Trisurat et al. (2010) applied a pixel size of 500×500m to a study area approximately 170,000 square kilometres. In these studies, the model was used to allocate approved land demand and to simulate land use change using the synergies between socio-economic and policy drivers. The studies had (natural) forest as one of the main land use categories, while only three categories of agricultural land use were distinguished (rice, upland crops, and tree crops). They simulated land use change using only Dyna-CLUE, but this single model was used to generate multiple future land use change scenarios. The authors chose Dyna-CLUE as it had prior successful application for allocating future land demand using both non-spatial and spatial features with various interrelating variables at multiple scales. The validation in these studies showed sufficient reliability to allow for subsequent simulations.

Example applications of Stochastic models:

CA-Markov is also a well-known and frequently chosen model to study land use change in Thailand. Boonchoo (2015) assessed land use change and its effect on the forest areas and attempted to identify an optimal geospatial land use land cover simulation model, using the CA-Markov module, Land Change Modeller (LCM module) and CLUE-S to analyse vulnerability to deforestation. The focus of the study was forest. The accuracy assessment of all three models (greater than 70%) was acceptable, however, CLUE-S was the most reliable. Chavanavesskul and Cirella (2020) compared the ability of the CA-Markov model and Land Change Modeller (LCM module) to simulate land use change, again with a focus on forest. The findings were similar for both methods which both showed high validation accuracy (especially in terms of agricultural and community areas).

Losiri et al. (2016) used CA-Markov and Multi-Layer Perception-Markov Chain (MLP-Markov) to model land use change and urban expansion in the Bangkok Metropolitan region. The accuracy of validations showed that MLP-Markov outputs had a higher accuracy than CA-Markov, and this study consequently used MLP-Markov for the simulation.

Example applications of Dynamic (process-based) models:

As an example of an application of ABM, Dumrongrojwatthana et al. (2009) applied ABM to represent the dynamic interactions between vegetation dynamics, reforestation efforts and livestock grazing using the co-construct approach. The output was used to design a hybrid simulator combining a role-playing game and a computer program by using the CORMAS platform. Walsh et al. (2013) and Malanson et al. (2014) also applied an ABM, but using a different approach and platform, to assess household income and wealth derived from agricultural production of lowland, rain-fed Rice, and upland field crops. These studies used the Repast platform and Java programming because they provided a flexible approach which allowed an experiment tool kit to be developed.

2.3.3 Research gap

The review of land use change models used in Thailand shows that most of the previous studies concerned deforestation and urbanisation (Akber and Shresta, 2013; Boonchoo, 2015; Losiri et al., 2016; Chavanavesskul and Cirella, 2020), while some models have been integrated with other models such as a biodiversity model (Trisurat et al., 2010; Sakayarote and Shrestra, 2019). Although, some studies were concerned with comparison of land use change models, none of the studies specifically focus on the agricultural land or the trends in individual crops (the exception to this is rice where it is a main crop in the study area and is identified as an independent category). None of these studies specifically focus on trying to model agricultural land use categories for their own sake, and this creates a gap in the research on land use change modelling. Can techniques used in deforestation or urbanisation studies be used to examine more detailed trends within the agricultural area? Can the land use change models which have been identified from the literature review be used to examine changes in the agricultural crops?

An international review of calibration and validation practices in land use models found that 31% of the applications did not report any model evaluation, while the rest were predominantly assessed in terms of their location accuracy, ignoring the uncertainty in the quantity and spatial patterns of land use (Verburg et al., 2019). Providing thorough evaluation though multiple methods is therefore an important consideration.

Many studies of land use change perform a simulation of the future after assessing the validation of the models using observed data. Few researchers have gone back in subsequent years to test the outputs of the simulation by observing the actual land use and seeing if the simulation was correct or not (Verburg et al., 2019), so this is another research gap. This study therefore seeks to assess simulations using additional information independent of the validation process.

As can be seen from the samples above, Dyna-CLUE and CA-Markov have become quite popular for land use studies in Thailand, but fewer studies have attempted to use other types of models and to compare their outputs.

Where there is a single model it is hard to assess confidence in the results because there is no point of comparison. This study therefore looks to compare several different models, to improve the research in this area.

It also aims to implement thorough evaluation of both model validation and simulation, while applying examples of several different types of models to the simulation of land use change. This study is particularly interested in trying to understand agricultural land use change in Thailand, however the findings may have broader applicability in as much as they provide evidence on how different types of models respond to this task (Chapter 6).

2.3.4 Initial land use model selection for the calibration stage in this study

The empirical-statistic models, stochastic models and dynamic (process-based) models all appear to be relevant to the research questions of this study as they predict and project the land use quantity and pattern. These types of model can also be used to help understand the drivers or causes of land use change, which is relevant to the research objectives. On the other hand, the emphasis of optimisation models on profit maximisation (such as yield or income maximisation) is less relevant to the research questions. This type of model is not used to project forwards, so is not so relevant to this study. Empirical-statistical, stochastic, and dynamic models are therefore worthy of future consideration.

Dyna-CLUE (an empirical model) was selected to predict the land use pattern in Thailand because this model has been successfully applied in other studies at a similar scale and is also suitable for dealing with multiple interacting variables. Moreover, this model has the ability to simulate the future land use under different scenarios by considering the statistical relationship between land use and the factor variables.

CA-Markov, CA-Markov with Multi-criteria Evaluation, Land Change Modeller (stochastic models) were also selected to investigate the relationship between observed land use patterns and the underlying bio-physical and socio-economic factors. This type of model, however, does not consider the behaviour of decision makers or agents. Agent-based models, on the other hand are designed to model exactly this aspect of the land use system, and this is also an interesting model to select as few of the previous studies in Thailand have utilised this model. In addition, including an ABM creates a broader basis for comparison between different type of models. For these reasons, an ABM (process-based model) was also selected.

Following consideration of the different types of model (Section 2.2.1), the criteria for model selection described above, and informed by previous work in this region (Section 2.3.2), a range of models were selected to test their efficacy for modelling land use change in Thailand. The selected models - Logistic regression in Dyna-CLUE (an empirical model), CA-Markov, CA-Markov with Multi-criteria Evaluation, Land Change Modeller, (stochastic models) and an ABM (process-based model) - will help to answer the questions of this study, such as, which models perform better for simulating land use change? (see Section 2.1 for more detail). Table 2.2. evaluates the various models which were selected for the calibration stage against the model selection criteria which were initially presented in Section 2.3.1. Details in the table were compiled from papers referenced in the literature review.

Table 2.2 An evaluation of the models selected for use in this study

Criteria	**Key characteristics**		
	Dyna-CLUE (see Briassouli, 2000; Verburg and Overmars, 2009; Lantman et al., 2011; Mas et al., 2014; Trisurat et al., 2019)	**CA-Markov, MCE, and LCM modules** (see Briassouli, 2000; Mas et al., 2014; Eastman, 2016; Tang and Di, 2019)	**ABM** (see Wilensky, 1999; Briassouli, 2000; Castle and Crooks, 2006; Niazi and Hussain, 2009; Valbuena et al., 2010; Liu et al., 2016)
Relevancy	- Model shows the land use allocation ability based on both spatial and non-spatial factors from different inputs such as land use demand, restriction area, land use conversion setting and location characteristics. - Simulation based on demand allocation for different land use categories.	- Model shows the two-way transitions among the available land use categories. - Model combines a spatial dimension with a neighbourhood effect. - Simulation based on historical maps using a transition rule.	- Model can simulate the future behaviour of the system and provide an approach which incorporates the behaviour of the farmers. - Simulation based on agent behaviours and decision making.
Applications and Technical	- Instruction document support. - Requires some land use modelling experience.	- Instruction document support. - Requires some land use modelling experience.	- Instruction document support. - Requires some land use modelling experience.
Data requirements (included resolution and temporal capability)	- Input data are flexible. - Input of land demand depends on another model. - Needs the expert's experience.	- Input data requires the historical maps from two periods and the variable factors. - Input data format is specific in its model. - Needs the expert's experience.	- Input data are flexible. - Model can exist to convert input data from other software formats. - Extensive and time-consuming data collection.
Linkage potential	- Allows input from other models such as a - Markov matrix which can be used for land demand.	- The results, in terms of a simulation map can be easily understood in GIS software.	- The results, in terms of a simulation map can be easily understood in GIS software.
Transferability	- No modification required	- No modification required	- No modification required
Output reliability	- Lack of reliability test for simulation process.	- Lack of reliability test for simulation process.	- Lack of reliability test for simulation process.
Model access and difficulty	- Difficult to implement without prior knowledge of advanced spatial analysis.	- User-friendly platform where users can follow the software menu. - Difficult to implement without prior knowledge of advance spatial analysis.	- User-friendly platform that can start from library provided and various samples. - Requires understanding of how to design and implement the model which needs programming code.

Most of the criteria show differences between the models. Regarding *relevancy* all the models have been applied to the problem of land use change in previous studies, but some models focus on underlying environmental variables while others are able to take human behaviour into account. All models in Table 2.2 would allow investigation of the influence of different factors on land use change and simulate it into the future. For this study, to meet the project aims, it was important to include examples of different types of model for comparison. Here, each of the models simulates the land use change differently (for example, see Table 2.2). In terms of *data requirements* Dyna-CLUE and MCE need expert experience, while ABM needs extensive data collection (i.e. survey data). Regarding *output reliability*, each model has its own accuracy and reliability performance (which can vary) but there is no simple reliability test for the simulation process (future simulation output) in any of the models. The validation process can however provide an indication of the reliability of the output. The validation of the models is described in Chapter 5. In terms of *model access and difficulty* CA-Markov, MCE and LCM have a user-friendly platform where users can follow the program menu, while ABM requires an understanding of how to design and implement a model which needs programming code. On the other hand, some of the criteria are similar, such as the linkage potential, where the results of the model can be understood in GIS software, and transferability, where none of the models require modification (the same method could be applied).

Most of the criteria for model selection can be considered before undertaking any modelling but for output reliability this can only be properly tested after the model has been run. To assess output reliability studies have focused on the models' accuracy or testing the 'Goodness-of-fit' results when comparing the prediction against reality (Congleton, 2001; Foody, 2002; Houet et al., 2016; van Vliet et al., 2016).

2.4 Summary

To summarize the review so far, the DPSIR framework shows the complexities of the biophysical and socio-economic system that must be analysed to understand land use change. Cause and effect relationships between the interacting factors (***Driving forces***, ***Pressures***, ***State***, ***Impact*** and ***Response***) are used to explain land use change as a relationship between the environment and the agents (or humans). Some land use models may consider the interactions better than other models.

The literature on land use change models shows that the models can be grouped into a variety of modelling practices and conceptual backgrounds. This framing provides a useful tool for comparison, particularly when one of the project aims is to test a range of models. The review here has found that empirical-statistic models are particularly good at identifying the association between land use change and different environmental or socio-economic factors, while Stochastic models are particularly good at indicating the transition potentials between pairs of land uses. Process-based (dynamic) models are particularly good at representing the behaviour of individuals (where this is likely to be important).

The models also vary in their temporal extent and ability to simulate land use in the future. Empirical-statistical models, for example, have a limited ability to extrapolate beyond the range of the input data, because they can only follow the historical trend; on the other hand, a dynamic model potentially has the ability to be more robust in its ability to capture changing circumstances.

It is evident that no single modelling approach has fully answered all the questions and needs of the land use planners and policy makers. The model selection assessed whether the models met the requirements to effectively model land use change. The criteria for model selection were; relevancy, applications and technical, data requirements, linkage potential, transferability, output reliability and model access and difficulty.

Land use models should be able to evaluate the different land use categories to model the dynamic process of land use change. The review of land use change models used in Thailand shows that most of the previous studies concerned deforestation and urbanisation. None of these studies especially focus on trying to model agricultural land use categories for their own sake. Can techniques used in deforestation or urbanisation studies be used to examine more detailed trends in the agricultural area? The need for more effort on validation and the assessment of simulations, particularly through the comparison of multiple models, was also apparent from the literature review. As a consequence, a range of models were selected to test their efficiency for modelling agricultural land use change in this research. These were Dyna-CLUE (logistic regression), CA-Markov, CA-Markov and Multi-criteria Evaluation (MCE) technique, Land Change Modeller (LCM), and Agent-based model. The calibration and validation of these models is described in the next chapter.

Chapter 3 | Methodology and case study design

In Chapter 1 a number of research questions were specified, and in Chapter 2 the approaches to land use change modelling were investigated. Land use monitoring concerns the trend of land use change from the past to the present, while the next step is the simulation. These changes relate to the driving factors which can be bio-physical or socio-economic. Monitoring and simulation are required because land use changes are directly linked to the ***Impact***, ***State*** and ***Responses*** of the DPSIR framework (introduced in Chapter 2).

This chapter first outlines the overall research design for the study. It then describes the data collection, which consists of data from primary and secondary sources. This is followed by the methodology section, which introduces the land use modelling software used in this study. The chapter then introduces the study areas, considering the characteristics of Thailand and the selection of study areas in detail. Finally, it concludes with an investigation and comparison of land use change in the selected study areas. This section answers the research question: 'How is land currently being used in the study area and how has land use changed in recent years?'

3.1 Research design and methodology

This study consists of three stages which are: research design, data collection and modelling. The section begins with a discussion of the research design (see Section 3.1.1). The data collection for this study involves the preparation and collection of primary and secondary data (see Section 3.1.2). The land use modelling software used in his study are described in Section 3.1.3.

3.1.1 An overview of the research design

This research focuses on the ability of different types of land use model to predict and simulate the possible (future) land use change in Thailand. It also compares the output reliability of (selected) land use models. The appropriateness of different land use models varies according to the application and simulation objectives (see the literature review in Chapter 2). Models typically compare the potential for different types of land use in both predictions and simulations.

An overview of the procedure for model comparison in this study is shown in Figure 3.1. The main research methodology consists of four stages which are (input) data collection (see Section 3.1.2), the calibration process (see Chapters 4), the validation process (see Chapters 5), and the simulation process (see Chapter 6).

The input data, for example the environmental variables and observed land use maps were used for model calibration (observations were between 2007 and 2012 for the first study area and between 2006 and 2011 for the second study area (see more detail in Section 3.1.2)). A land use change model uses the software (see more detail in Section 3.1.3) for land use prediction of the land use map in 2015 and 2016, which forms part of the validation process. Simulation results (of land use maps for 2025) follow successful validation and allow comparison of the selected models.

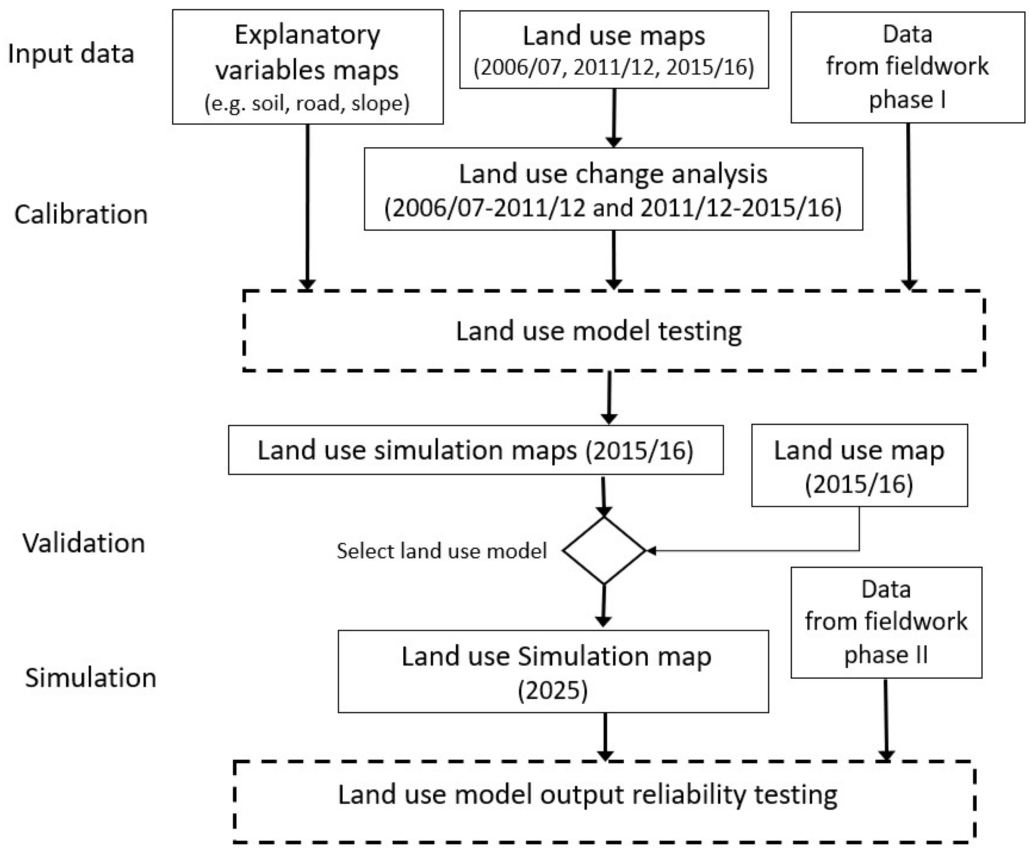


Figure 3.1 The modelling structure used in this study

3.1.2 Validation accuracy assessment

The benefit of a land use model depends on the precision and accuracy of the model outputs, and it is necessary to evaluates these in order to improve their ability to explain the real world (Pontius et al., 2008; Verburg et al., 2015). Land use change validation refers to an assessment of how it performs for the intended purpose (Houet et al., 2016; Vliet et al., 2016). There are also challenges in relation to certainty, complexity, and the non-stationarity of the land change process (Vliet et al., 2016).

The comparison of the model validation has many steps such as visual inspection of the map, creation of difference maps between the reference and simulation maps and quantitative accuracy assessment by error matrix (Congalton, 2001; Foody, 2002; Paegelow et al., 2014). Common validation and error analysis techniques use a map comparison technique, i.e. a cell by cell comparison between simulated and observed land use change (Pontius et al., 2008; Paegelow et al., 2014; Rosa et al., 2014). The result is often a map where land use category prediction was correct (in an individual cell) or incorrect.

The model validation by visual inspection is a simple yet important step that performs an assessment of the simulated map by looking at the fit of the results compared with the reference map. This correct/incorrect map (or binary map) makes it very clear where the simulation map has successfully predicted the features on the ground. However, this method needs additional validation by the creation of difference maps between the reference and simulation maps to evaluate the map error (Paegelow et al., 2014).

Many studies calculate validation statistics by a cross-tabular comparison (or error matrix) of the reality or reference map and the simulation map. This presents the accuracy of mapping or modelling results by stating the accuracy for each category in terms of the percentage of cells, which were correctly predicted.

For the simulation accuracy assessment, the results can be evaluated with accuracy matrixes (see example in Figure 3.2). The diagonal of the matrix indicates the correctly classified cells when comparing the actual map (or reference map) with the simulation map. The accuracy metrics calculate overall accuracy, user's accuracy, and producers' accuracy values (Morisette and Khorram, 2000; Pontius et al., 2008).

		Reference map			
		Forest	Urban	Agricultural	Row Total
Simulation map	Forest	25	3	4	32
	Urban	7	24	4	35
	Agricultural	8	3	22	33
	Column Total	40	30	30	100

Total number of the major diagonal = (25+24+22) = 71

Overall accuracy = 71/100 = 0.71 (71%)

Producer's accuracy		User's accuracy	
Forest	= 25/40 = 0.63 (63%)	Forest	= 25/32 = 0.78 (78%)
Urban	= 24/30 = 0.80 (80%)	Urban	= 24/35 = 0.69 (69%)
Agricultural	= 22/30 = 0.73 (73%)	Agricultural	= 22/33 = 0.67 (67%)

Figure 3.2 An example of an error matrix for accuracy calculation

Overall accuracy indicates what the overall percentage of correctly mapped cells is, as the diagonal element presents the areas that were correctly predicted in each land use category. Overall accuracy is calculated as the total number of correctly predicted values divided by the total number of values (Morisette and Khorram, 2000).

The producer's accuracy calculates the correspondence between the simulation map and the reference map. It can explain how often the result of a reference map is correctly classified or well-mapped (Morisette and Khorram, 2000; Pontius et al., 2008). It is calculated by the number of correctly classified cells divided by the number of cells, in the category on the reference map. To put it simply, it measures how often cells in a particular category in the model are predicted correctly. A perfect simulation, where each cell is predicted correctly, would give an accuracy of 1.0 or 100% (Morisette and Khorram, 2000; Dzieszko, 2014; Food and Agricultural Organization, 2016).

The user' accuracy measures the correspondence between the observed data and the simulation, that is the proportion of a particular category on the ground that is also in the same category in the simulation map. This is expressed as the actual number of cells within a particular category divided by the total number of simulated cells in the same category. To put it simply, this shows how often the features on the ground are correctly predicted by the simulation (Morisette and Khorram, 2000).

The error matrix not only computes the primary accuracies, such as the producer's accuracy, user's accuracy and overall accuracy but can also be used to calculate the average producer's and user's accuracy by using the arithmetic mean of the producer's and user's accuracy. This is used to interpret the land use categories to rank them in order of accuracy (Liu et al., 2007).

The extent of difference in the producer's and user's accuracy can be assessed using Spearman's rank correlation (Rogerson, 2010).

3.1.3 Data collection

The preparation and collection of data is an important step in land use change modelling. This study required both primary and secondary data, which are shown in Table 3.1. The input data which can be obtained is important to the success of the model, while special types of data are necessary for some models (such as ABM) so that the decision-making of the farmers can be incorporated into the modelling process. Therefore, in this study, fieldwork was required to obtain the relevant information.

In this study, the primary data were collected via questionnaires surveys and interviews, while the secondary data were collected from statistical datasets and published reports, such as the demographic and climatological data shown in Table 3.1. A field survey was chosen as a technique to consider the farm practices and to understand the driving factors and the decision-making of farmers. The field survey consisted of interviews and conversations with the farmers and the land use experts in Thailand.

Table 3.1 Digital spatial data sources

Data	Scale/Years	Data Sources
Land use maps	1:25,000	Land Development Department
Soil map	1:25,000	Land Development Department
Digital Elevation Model (5m)	1:4,000	Land Development Department
Stream map	1:25,000	Land Development Department
Road map	1:25,000	Land Development Department
Administration boundary map	1:4,000	Department of Provincial Administration
Climatological Data (30 years)	1986-2016	Thai Meteorological Department

Table 3.1 summarises the secondary (digital spatial data sources) for this study. These data were used for the calibration process, including as variable factors (see more in Chapter 4). The spatial data sources in this research consisted of digital maps namely: land use maps (years 2005, 2006, 2011, 2012, 2015, and 2016 (for more detail see Section 3.3), soil map (updated 2010), Digital Elevation Model (DEM), roads map, streams map, administration boundary map (updated 2012) and climatological data (30 years). The road and stream maps were derived from the soil data system in Soil View version 2.0 (Land Development Department, 2000). These data included relevant biophysical and socio-economic data that supported developing options for the model scenario and understanding of the driving forces. These were in Universal Transverse Mercator projection (UTM Zone 47).

In terms of fitness for purpose, the data cover a wide range of variables which could potentially influence land use. The study worked with a detailed land use map which was equivalent to the level three land use classification in Thailand - which maps individual crops (See Section 3.3). The scale of this data captured quite a fine level of detail (including individual fields). Some of the data are presented in categorical rather than continuous datasets for example, the soil data. This makes it more difficult to calculate statistical relationships. The soil map refers to soil fertility and soil drainage, but these attributes are categorical. The mountainous areas with steep and complex slopes are not included in the soil data due to the difficulty of surveying. These areas are in any case reserved for forest. Some data such as rainfall do not show great variation across the study area so are unlikely to be strong predictors at the level of the Sub-watershed. This data is still useful to include though. Distance to river can indicate the potential for irrigation or flooding, but it is an imperfect indictor for these factors. If more specific data was available or irrigation for flood risk this would be helpful.

Field surveys

The field survey data was collected from two different groups of people using questionnaires. The first group consisted of a sample of farmers who grow the main crops in each study area (the main crops are described in Section 3.3). The selection of the farmers for the study is described below. The second group consisted of land use experts from the Land Development Department in Thailand. This is the main government agency responsible for land use planning in Thailand. A land use 'expert' is defined in this study as an individual with significant relevant experience and qualifications within the Thai Government (e.g. the Land Development Department). These experts all had direct field experience (at least 15 years) of agricultural activities and land management issues (knowledge in soil sciences, agricultural sciences, and agricultural economics) in the study regions.

The data collection in the field survey consisted of two stages. The first survey formed part of the calibration stage (this was phase one of the fieldwork conducted during 2017), while the second stage related to the findings of the simulation stage (undertaken during 2019 and 2020).

Calibration stage

The first group of interviewees consisted of individual farmers who were each representative of a single household. The sample size for the study was 50 farmers for each study area. Figure 3.3 presents the method which was used to recruit the farmers in the study areas.

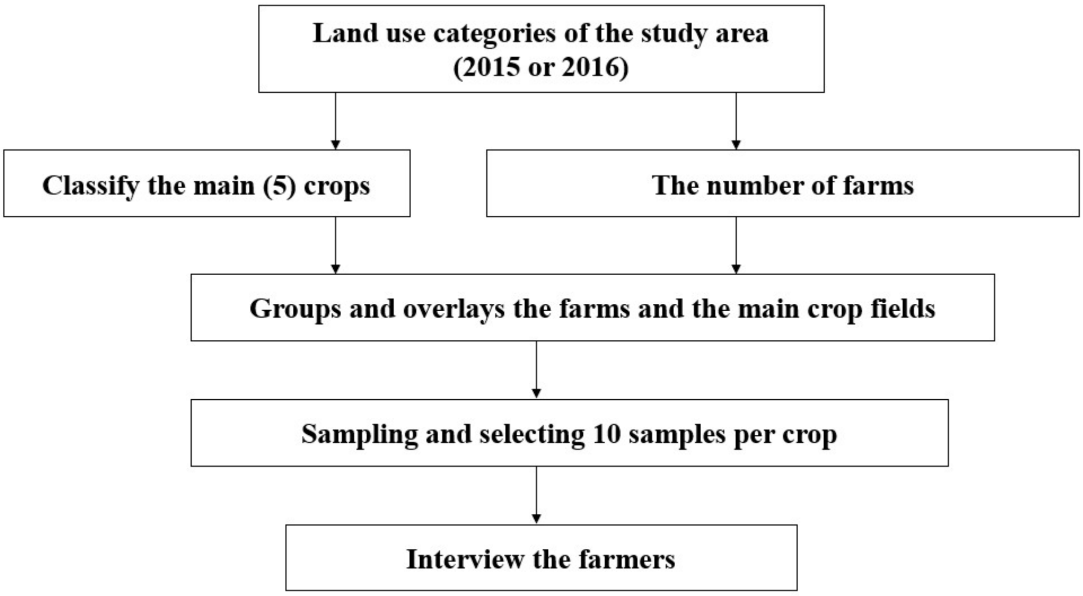


Figure 3.3 The method to recruit the farmers for the samples (total of 50 farmers for MCSW and 50 farmers for LMSW) at the calibration stage.

The flowchart describes the concept which was used to recruit the farmers for the survey for the first stage. The selection and sampling criteria for the interviews related to the characteristic of the farmers (i.e. farm size, farming experience) and the type of crop they grow. In order to select farmers, the five main agricultural categories in each area were analysed from the land use map (year 2015 or 2016) using ArcGIS. The results provided evidence of the range of agricultural activities and where each activity was located.

Another important aspect was to survey the number of households who grow the main crops in the study area using data from the local government agency concerning farming households. The next stage was to group and overlay the farmers and the map of the main crops to select a specific village or community (cluster sampling).

The local government agency was able to provide guidance on the number and the identity of the farmers in the area, which narrowed the focus of the sampling to select the interviewees who were needed.

The farmers were interviewed to obtain the primary data concerning the agricultural activities, crop yield, land tenures information, the problems relating to agricultural activities, the decision making about their crops, plan to use land in the future, and farmers' general information (this information for ABM is discussed in Section 4.4).

The second group of interviewees consisted of eight land use experts. The interviewees scored and ranked the variable factors influencing land use according to their perceived importance. This information was used in the multi-criteria evaluation (MCE) module. Three land use experts (from the same group) also scored the elasticity conversion numbers (to support the land use type-specific conversion setting of Dyna-CLUE (see Section 4.2)). This allowed the average results of the elasticity conversion numbers to be calculated.

Simulation stage

After the simulation results (the land use maps for 2025) were obtained from the selected models, it was necessary to evaluate their plausibility (see Chapter 6). Part of this process was to interview six land use experts (from the same group as above) at the Land Development Department, including local experts from regional officers.

The interviews concerned what the likely trend in each crop would be over the next 10 years (to 2025) in each study area. The experts were asked if they thought each crop would increase, decrease, or stay the same. They were also asked to score and rank their agreement with the land use simulation outputs, and the plausibility of the simulation for each model. The experts were asked to score the models on a scale of one-to-nine with one being the least satisfactory/suitable and nine the most satisfactory/suitable.

3.1.4 Models and software used

This research focuses on the ability of different types of land use models to predict and simulate the possible (future) land use change in Thailand. The appropriateness of different land use models varies according to the applications and simulation objectives (see the literature review in Chapter 2). There are many land use modelling software packages. These software tools contain different functions, which are possibly useful and appropriate depending on the available input data and the modelling objectives. (Mas et al., 2014).

The land use models which were selected for the simulation of the land use change pattern were Dyna-CLUE, CA-Markov, MCE, and LCM modules, and ABM. These tools could process the input data, which is relatively uncomplicated and easy to assess when using the available tutorials and instruction manuals.

The study also sought to simulate future land use change. Collecting data on the crops grown over the period can be used as a tool to help understand crop specific decision making. The dynamically simulated model is used to predict and simulate the land use change which can help to understand the influence of the driving forces and the reason for land use change. These methods can be complemented by the analysis of multi-objectives, considering the past and the future requirements of different stakeholders.

Dyna-CLUE is a specifically developed model for land use analysis in small regions such as provinces or watershed at a fine spatial resolution. This model can be set up based on survey data and expert knowledge. Dyna-CLUE is subdivided into four categories; spatial policies and restriction, land use type specific conversion setting, land use requirements, and location characteristics. All four categories together create a set of conditions and possibilities for model prediction (Verburg, 2002) (See more detail in Chapter 4).

IDRISI TerrSet software includes a CA-Markov module, Multi-Criteria Evaluation (MCE) module and Land Change Modeller (LCM) module. CA-Markov in IDRISI uses the Markov matrices to determine the number of changes, alongside a suitability map, which is based on the historical maps. A CA process is used to spatially allocate the changes for the prediction (Eastman, 2016).

The MCE module in IDRISI is used to analyse land use change. The MCE empirically models the relationship of the land use to explanatory variables, and simulates future changes, which the Markov chain matrices and transition potential maps obtain by training the machine learning. MCE uses a two-dimensional CA consisting of the historical land use changes and the driving factors, which is used to generate the suitability map. The suitability map is prepared by aggregation of a collection of land use categories based on the MCE method. The MCE is a common method for aggregating and evaluating weighted map criterion based on expert knowledge (Eastman, 2016) (see more in Chapter 4).

LCM module in IDRISI also is an empirical model that relates to explanatory variables and future simulation. The LCM uses a transition potential map which is based on the probability of a land use category changing to another land use category. The categories are grouped into a set of sub models and explore the influence ability of explanatory variables. (Eastman, 2016) (see more in Chapter 4).

The modules in IDRISI represent several approaches of increasing sophistication for obtaining prediction and simulation outputs. The CA-Markov model created the transition potential maps or suitability maps from the historical maps while MCE and LCM create this map from the driver variables.

The Agent-based models (ABM) determines the dynamic system of behaviours of the agents. ABM also demonstrates the decision-making and the interaction of the agents (the land users). The ABM software in this study is NetLogo (Wilensky, 1999) which is compatible with GIS and is open-source software. NetLogo is an Agent-based model for social and natural sciences. NetLogo is applied as an ABM because it is a multi-agent programmable model which is suitable for the simulation of complex phenomena (Crooks et al, 2019) (see more in Chapter 4).

3.2 The study areas

Thailand is located in South-East Asia boarding the gulf of Thailand; the Andaman Sea, Myanmar, Laos, Cambodia and Malaysia. It is situated at a latitude of around 5° 37′ and 20° 27′ North and longitude of around 97° 22′ and 105° 37′ East (see Figure 3.4). The total area of the country is approximately 513,115 square kilometres. Thailand is divided into five regions in administrative and statistical contexts, climate pattern and meteorological conditions as well as five cultural groupings, which are Northern, North-eastern, Central, Eastern and Southern. Administratively, the country consists of 77 Provinces.

Figure 3.4 The location of Thailand (topographic map from Google maps)

The climate of Thailand (Thai Meteorological Department, 2017) is under the influences of seasonal monsoon wind. The climate of Thailand is divided into three seasons; rainy (or southwest monsoon) season that is between mid-May to mid-October, winter (or northeast monsoon) season that is between mid-October to mid-February, and summer (or pre-monsoon) season that is between mid-February to mid-May.

The southern monsoon begins in May, bringing a storm of warm, humid air from the India Ocean to the land, causing abundant rain across the country, particularly on the windward side of the mountains. Rainfall during this time is not only caused by the southwest monsoon, but also by the Inter Convergence Zone and tropical cyclone, which generate a large amount of rainfall. The Northeast monsoon begins in October, bringing the cold and dry air from the anticyclone in China to the majority of the country, particularly the northern part of the northern region, which is a higher latitude area.

The temperature in Thailand in all regions except the southern region typically has a long period of warm weather due to its inland location and tropical latitude. Between March and May is the hottest time of the year when the maximum temperature normally reaches 40 degrees Celsius or more. The beginning of the rainy season often dramatically decreases temperatures from mid-May and is typically below 40 degrees Celsius. On the other hand, in the southern region, the temperatures are usually mild throughout the year due to the maritime characteristics of the region.

Rainfall in Thailand is reduced in the winter due to the northeast monsoon, which is the key factor influencing the climate in the region. The summer period is marked by a gradual increase in thunderstorm rainfall. The onset of the southwest monsoon leads to heavy rainfall from mid-May until early October. Rainfall peaks are in August or September, which usually causes local flooding. According to a general annual rainfall trend, most areas of the country receive between 1,200 and 1,600 mm per year.

The topography of Thailand has been divided into five regions (Thai Meteorological Department, 2017). The topography of each region is very different. The five regions of Thailand are shown in Figure 3.5.

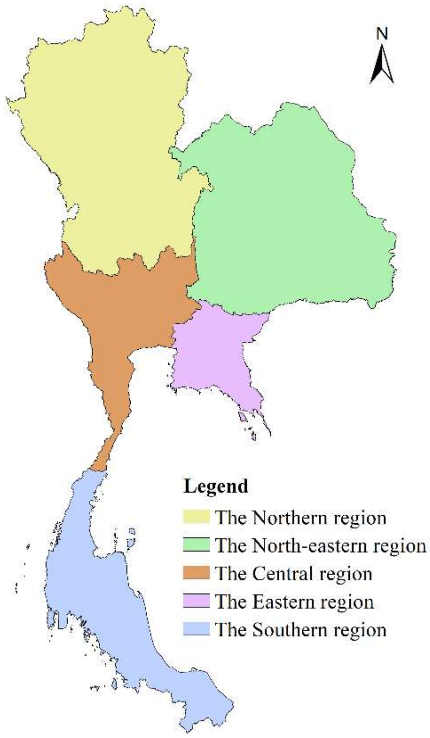


Figure 3.5 The five regions of Thailand

In the Northern region, the majority of the land consists of hills and mountains, which are the source of many important rivers (such as the Ping and Nan Rivers). The mountains consist of parallel north-south hill ridges which are intersected by a group of major valleys (or inter-montane basins) such as those in Chiang Mai, Chiang Rai, Lampang and Nan provinces. The highest mountain (Doi Inthanon) is approximately 2,595 metres above mean sea level.

The North-eastern region consists of a high-level plain which is referred to as the north-east plateau. Culturally this area is known as Isan. The area forms part of the greater

Mekong drainage basin. This region has two distinct parts. The first part consists of a high-level plain in the west, while the second part consists of the slopes towards the east.

The Central region is a broad, low-level plain. The Central regions is bordered by the western mountains (to the west) and the highlands (to the north). The most important river within the Central region is the Chao Phraya River. Bangkok (the capital city) is located within the Central plains.

The southern and south-western part of the Eastern region are adjacent to the Gulf of Thailand. Farther inland, the topography generally consists of plains and valleys, although there are some small hills in the northern, central, and eastern parts of this region.

Lastly, the Southern region consists of the parts of the Kra Isthmus – situated between the Andaman Sea on the western side, and the Gulf of Thailand on the eastern side – which are within the Kingdom of Thailand. The long mountain ridge (the Tenasserim range) which begins in the northern region and extends along the western edge of Thailand also extends to this part of the country.

The population of Thailand in 2016 was 65.93 million people. This is equivalent to 0.91% of the world population, and the population has significantly increased in the last decade (from 61.87 million in 2000) with an annual increase around 0.22%. The population density of the country is approximately 134 people per square kilometres whilst the number of Thai households is around 23 million households and the urban population is 51% (Department of Provincial Administration, 2017).

In terms of economics, in 2016, the Gross Domestic Product (GDP) was 577.51 billion US Dollars. The GDP per capita was recorded in 2016 at 15,346.65 US dollars (Office of the Nation Economic and Social Development Board, 2017). Based on figures provided by the International Monetary Fund (IMF), Thailand was ranked as the 31st largest economy in the world while the USA was the first ranked (18,561.93 billion US Dollars) and the United Kingdom was the sixth ranked (2,649.89 billion US Dollars). In addition, the GDP from agriculture in Thailand was 22,622 billion US Dollar. Agriculture remains an important sector within the Thai economy. As an illustration, for the products of rice, cassava, sugarcane, palm oil, coconut and pineapple, Thailand is one of the ten largest exporters in the world. Thailand is the second largest producer of cassava in the world. Rice is a very important crop in Thailand and the country is the biggest exporter of rice in the world after India (Office of Agricultural Economics, 2017; Office of the Nation Economic and Social Development Board, 2017; International Monetary Fund, 2016).

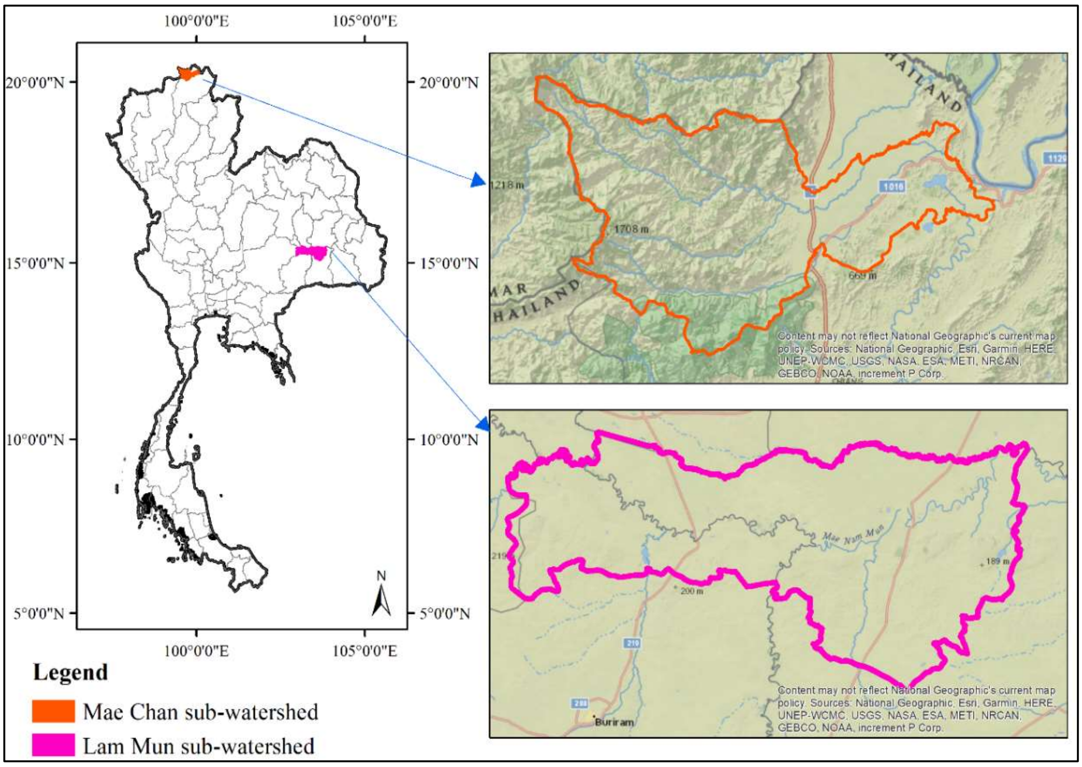
Thailand is one of the top agricultural producing countries alongside the USA, China, India, and Brazil. Some countries like China and India feature prominently in the rankings of the top agricultural producers, but these counties have a huge population, thus a major priority of their production is to supply the domestic market and ensure internal food security. However, focusing on the capacity for food support to the world and looking at important products such as rice, maize, beans, livestock and fish, Thailand features more prominently in the top of the rankings (United States Department of Agriculture, 2017).

Thailand is a good example of an important food producer and exporter, though, the country also has many challenges in term of land use management. Agricultural land is being lost to non-agricultural uses and the country is faced with the effects of climate change and population growth (Chomchan and Nopparat, 2018). The total agricultural land throughout Thailand decreased from 56.07% in 2000 to 55.73% in 2017 (Land Development Department, 2017). Thailand is an interesting country to apply an agricultural land use change model to because it has a high level of biodiversity and much crop production is related to variations in the climate, topography, and soils. According to the Thai governments' policy 'Kitchen of the World' (Board of Investment Thailand, 2012), some development economics experts suggest that the African countries should look to Thailand as an ideal model of food supply development to learn how to apply the lessons of agricultural driving forces to regional trade. In particular, Thailand has a complete food market driven supply system and most of the raw materials for the food sources can be produced within the country (Plaajes, 2014).

The aims of this study were to investigate the performance of different modelling software and the pattern of land use change in Thailand. To discuss patterns of land use change, it was also important to consider regional differences. Thus, it was decided to compare two area that varied in their geography, size, and main crops. This allowed the performance of the models to be assessed in different contexts. The physical differences between the study areas potentially allow for broader conclusions to be made (e.g. this type of model performs well in this circumstance, but not in these etc.). The number of study areas had to be limited to two because of the amount of time required to implement and assess the models. Ultimately, it was decided to focus on two sub-watersheds from the Northern and North-eastern regions.

The North-eastern region is an important rice growing region and Buriram and Surin provinces are among the top five provinces in terms of rice harvest. Lam Mun Sub-watershed (which takes the part of Buriram and Surin) was selected as good study area to represent this region. In the North region the Mae Chan Sub-watershed was selected because it features different upland crops and is typical of more mountainous areas within Thailand. This contrast between the study areas made a good basis for comparison. The researcher also had personal work experience of these areas and some good local contacts which were helpful to understand the land use issues in more detail.

Thailand has 25 main watersheds divided into 254 sub-watersheds. The definition of sub-watersheds depends on geography, ecosystems, hydrological conditions, urban planning, and administration boundaries. The Mae Chan Sub-watershed (MCSW) is a part of in the Khok watershed and is located in Chiang Rai province. The Lam Mun Sub-watershed (LMSW) is a main part of the Mun watershed (and incorporates part of Surin province and Buriram province), hence this area is called the Lam Mun Sub-watershed or LMSW. These Sub-watersheds form part of the Mekong basin. The areas, MCSW and LMSW, (Figure 3.6) were selected because of the significant differences in geography, environment, and farming practices between the two zones (see more in Sections 3.2.1 and 3.2.2).



The study areas, the first study area is Mae Chan Sub-watershed (MCSW) and the second is Lam Mun Sub-watershed (LMSW)are marked by orange and pink outline on the map of Thailand (topographic map from Google Maps).

Figure 3.6 The location of Mae Chan Sub-watershed (MCSW) and Lam Mun Sub-watershed (LMSW)

3.2.1 The study area: Mae Chan Sub-watershed (MCSW)

Mae Chan sub-watershed (MCSW) is located in the north of Thailand and has a total area of 1,291 square kilometres. MCSW is between 20˚ 2′ 8″ and 20˚ 23′ 40″ North and 99˚ 27′ 29″ and 100˚ 7′ 19″ East. The population was around 180,000 people and the density of population was approximately 145 people per square kilometres in 2016 (Department of Provincial Administration, 2017). In this area, the population decreased from 2007 to 2016 by approximately 1,500 people or 0.8%.

The boundary covers Mae Faluang district, Mae Chan district and Chiang-Saen district, within the Northern part of Chiang Rai province. Mae Faluang district borders Myanmar while Chiang- Saen district borders the Mekong River, which separates Thailand from Laos (Figure 3.7). The northern and western edge of the sub-watershed borders Shan State in Myanmar. This area is mountainous and there are few border crossings. The main border crossing is at Mae Sai/Tachileik, which is outside the study area. The topography of Mae Faluang is hilly with an elevation of up to 1,200 metres above sea level. The western part of the study area is a hilly region with a series of hill ridges orientated north to south in Mae Chan district and Chiang-Saen district. Between the two hilly areas is a wide plain (Department of Provincial Administration, 2017).

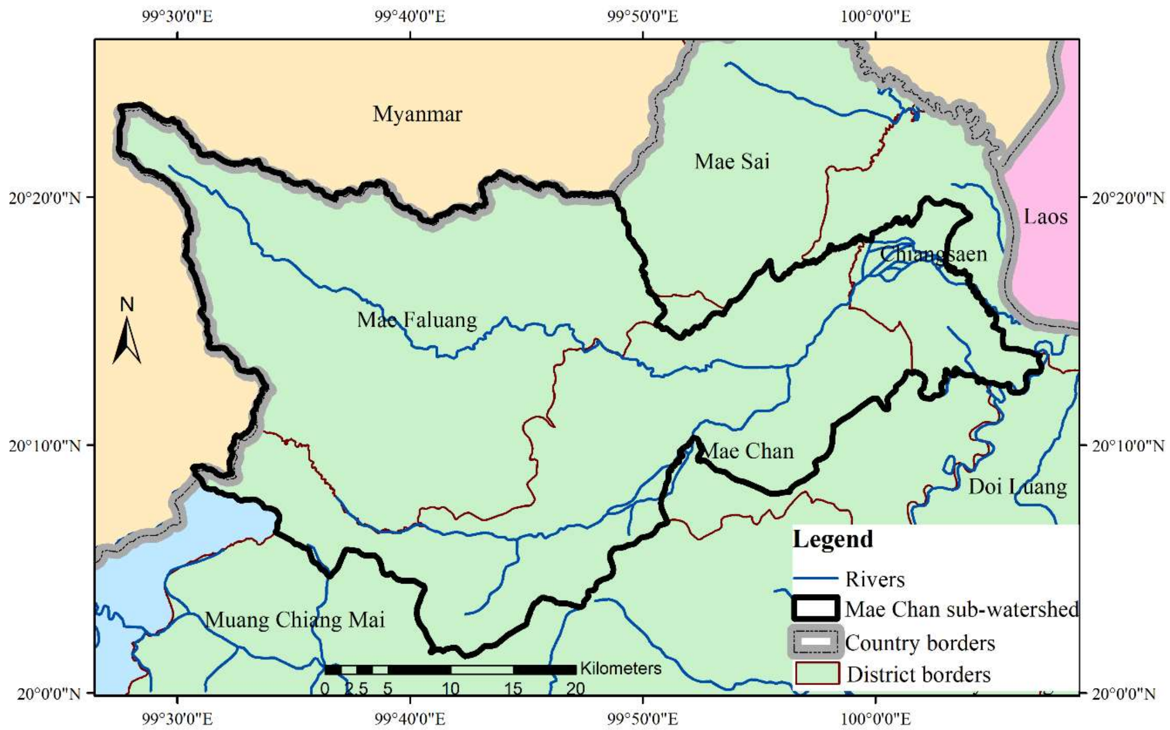


Figure 3.7 The location of Mae Chan Sub-watershed (MCSW)

In terms of climate, the main rainy season in this area is from May to August with the monsoon season running from late April through to October. Temperatures average approximately 15 Celsius in winter (November to February) and increase to about 37 Celsius in summer (March to May). Water remains in the Mae Kham and Chan Rivers throughout summer, and there is sometimes localised flooding during the rainy season (Thai Meteorological Department, 2017). This area has a high capacity in terms of agricultural productivity to support domestic and international consumption of products such as rice, maize, coffee, tea, pineapple, orange, longan, and lychee.

The area also has a number of land resource problems such as land misallocation (where land which is suitable for agricultural uses is occupied by urban), shallow soil and soil erosion, flooding, drought, and deforestation. Also, the infrastructure is being improved as the main road from the centre of Chiang Rai (Thailand) to Myanmar is expanded as part a wider road network connecting the countries in the Greater Mekong Sub-region (GMS) comprising Thailand, Myanmar, Laos, Cambodia, Vietnam, and China. This environmental change and the policy of infrastructure development can have an effect on land use conversion. The land use changes include not only deforestation for cropping, which is the main land use problem, but also changes which result from tourism, which is one of the most important industries in this area. There are cultural tours and agricultural tourism, which attract many tourists (Chiangrai Governor Office, 2017; Office of the National Economic and Social Development Board, 2017; Department of Provincial, 2017)

3.2.2 The study area: Lam Mun Sub-watershed (LMSW)

The second study area is the Lam Mun Sub-watershed (LMSW) which is located in the North-East of Thailand and has a total area of 2,789 square kilometres. The latitude of LMSW is between $15^{\circ}2' 50''$ North and $15^{\circ}28' 54''$ North and the longitude is between $102^{\circ}56'54''$ East and $103^{\circ}53' 25''$ East. In 2007, the population was around 620,000 people and the density of population was approximately 224 people per square kilometre. Between 2007 and 2016, the population increase by approximately 7,000 people, or 1.1%.

The boundary of this area includes parts of Surin province and Burirum province. It covers Satuk district, Khaendong district and Khu Muang district in Buriram province, as well as Rataburi district, Sanom district, Thatum district, Chompra district and Chomphon Buri district in Surin Province (Figure 3.8). The topography is high plain and nearly flat to undulating, at an elevation of about 240 metres above sea level (Department of Provincial Administration, 2017).

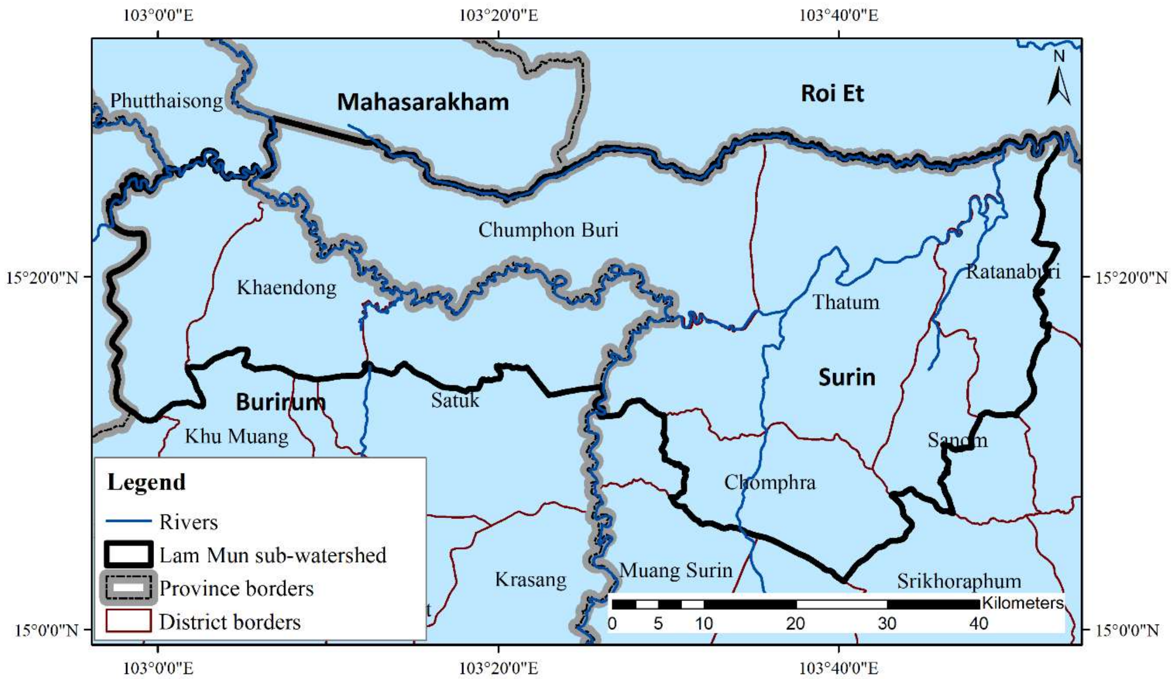


Figure 3.8 The location of Lam Mun Sub-watershed (LMSW)

In terms of climate, the main rainy season in this area is from May to October with the monsoon season running from mid-May through to mid-October. Temperature average approximately 22 Celsius in winter (October to February) and increase to around 37 Celsius in summer (February to May) (Thai Meteorological Department, 2017). This area has a capacity in terms of agricultural productivity to support domestic and international consumption of products such as rice, sugarcane, cassava, maize, and mango.

The study area is located in a specific problem area, with most of the area featuring sandy soils or sandy loam soils and inland saline soils called "Tung Kula Rong Hai". The farmers not only face flooding in the rainy season but also face drought in the cropping season and at the end of the rainy season. Since 2006, the agricultural area has rapidly changed to urban area over 3% of the total area, and former paddy field areas have changed to cassava, sugarcane, and rubber. Surrounding the LMSW are three sugar factories, which each have a high demand for sugarcane of approximately 18,000 tons per day. Some of the factories can produce electricity (from biomass crops) and the increase in biomass crops will affect rice production in the future (Land Development Department, 2017; Office of the National Economic and Social Development Board, 2017; Department of Province Administration, 2017).

3.2.3 The agricultural situation in the study areas

The previous section concerned the characteristics of the study areas. This section discusses the characteristics of the main crops in the study areas (such as Rice, Maize, Pineapple, Coffee and Tea, and Rubber in MCSW, Cassava, sugarcane, and Eucalyptus in LMSW).

Rice:

Rice is an important crop in Thailand as a traditional staple food and it is also the most important crop for export to the world market. Originally, Thai farmers grew rice to feed their family and kept some gains for the next crop, which is a traditional method of farming inherited from their predecessors. In addition, the history of cropping in Thailand establishes that rice has been grown for many years and is a traditional crop since 2000-1500 BCE which is based on evidence from rice-tempered pottery (Castillo, 2011).

Rice can grow in all provinces of Thailand but more than 50% of the total area of rice is in the north-eastern region. Surin and Buriram provinces (which LMSW is located in) are in the top five provinces in terms of the largest rice harvests. The main season lasts from May to December (the wet season) while planting takes place between May and July, and harvesting between November and December (FAO, 2002).

The most famous rice exports to the world market are Thai Jasmine rice or “Hom Mali Rice”, white rice and parboiled rice. Most of the areas in the Northern and the North Eastern region grow jasmine rice (Department of Agricultural Extension, 2018). However, the yield from the area named “Tung Kula Rong Hai” in LMSW area is famous and celebrated because it is more fragrant than rice from other areas in Thailand. This is because of the geography, which features sandy soil that has a high concentration of sodium and silica. The soils of these areas are low fertility and saline soils. The weather and soil conditions create soil stresses, and the soils release an aroma compound (2-Acetyl-1-pyroline or 2AP) which affects the scent of the jasmine rice (Changsri et al., 2015). The Thai government announced the Rice Insurance project (in 2009) and the Rice Mortgage project (in 2011) which ensured a minimum price for Rice which was higher than the market price. Thus, the project could encourage farmers to continue farming (Chomchan and Nopparat, 2018). The scheme ended in 2014.

Maize:

Since World War II, many of the large reductions in the area of Forest in Thailand are due to expansion of Maize. Maize is a crop which has been promoted for the animal feed industry since 1953. The area of Maize in Thailand in 1954 was around 53,000 hectares. The area of Maize continued increasing until it reached approximately 1.7 million hectares between 1987-1991. This was because, at this time, Maize achieved a better price than Rice cultivation, as well as using less labour in the field. Moreover, new areas of Maize were largely established in the Northern part of Thailand, especially in the hilly areas that are not suitable for Rice, or other economic crops. Thus, these areas came to be used for Maize cultivation. The increase of the area of Maize is due to the attractive market price and relates to the contract farming condition - where incentives (such as seeds, fertilizers and loans) are provided by a large company - and to government policy, such as the Maize Price Insurance Project, which was operational in 2009/10 (Chomchan and Nopparat, 2018).

Maize mostly grows in rain-fed areas that have two main planting seasons, the first crop being grown between May and September, and the second crop between August and December (Ekasingh et al., 2004).

Pineapple:

After 1977, the farmers in Chiang Rai province started to grow pineapple (Department of Agricultural Extension, 2015). The land use map from the year 2001 by the Land Development Department shows that in Chiang Rai province the area under pineapple cultivation was about 1,070 hectares. Since 2013, the market price of Pineapple for suppling the food processing factory (for canning) has fluctuated (Food Intelligence Center Thailand, 2020). The processing factories are located the southern region of Thailand (Prachuap Khirikhan province). The expansion of the area of Pineapple can be explained due to Pineapple growing well, as Pineapple does not need much water, and the attractive market price, especially for fresh eating in the domestic market. This is because the Pineapple of this area (Phulae variety) has unique characteristics as a Geographical Indication of Chiang Rai (Office of Agricultural Economics, 2017; Department of Intellectual Property, 2018). Geographical Indications (GI) are a name or sign used on a product to indicate a specific geographical origin. Geographical Indications are used where the quality, reputation or other characteristics of a product can be determined by where it originates (World Trade Organization, 2020). Pineapple can be planted at any time of the year. It takes approximately a year and half to go from a new plant to flowering, and then another 3-4 months for the flower to turn to fruit (Joomwong and Sornsrivichai, 2005).

Coffee and Tea:

The Thai government have promoted Tea plantations in the highlands since 1990. Coffee was introduced as a major economic crop in 2002, after the government's strategic plan promoted growing coffee and tea instead of other crops in the highland. The area in Chiang Rai province (which contains MCSW) is suitable for Coffee. The market for coffee has continued to expand since 2011, thus the demand for Coffee has also increased (Department of Agriculture Extension, 2018). Between 2009 and 2013, the Department of Agricultural Extension, Thailand launched a project to teach farmers about Coffee production (Coffee production knowledge) (Department of Agricultural Extension, 2012).

Coffee and Tea are perennial crops. Individual Coffee and Tea bushes can provide a yield for longer than 20 years. The time for Coffee from planting to the first harvest is approximately 3 years while for Tea the time from planting to the first harvest is approximately 3-4 years (Highland Research and Development Institute, 2016a; 2016b).

Rubber:

In 2004, the Thai government adopted a policy to promote and extend rubber in the Northern and North Eastern regions of Thailand, for which the target was 1,000,000 rai or 160,000 hectares. This policy involved subsidy, and other public goods, provided by the government (such as loans, young Rubber plants and knowledge by training) (Rubber Authority of Thailand, 2018). The Tsunami in Japan in 2011 caused disruption in the demand for Rubber, Also the trend of the Rubber yield was continuously increasing, thus these situations affected the market price later (Land Development Department, 2013). Rubber is a perennial crop that can provide a yield for 25-30 years but the time from planting to the first harvest is approximately 6-7 years (Forestry Industry Organization, 2007).

Cassava:

In 1960, Thailand started exporting cassava to Japan, USA and the neighbouring countries which lead to the expansion of cassava in the North-eastern region, especially in LMSW. In early years, the cassava exports focused mainly on products in dried chip or starch power form. The farmers grow cassava on areas which are unsuitable for paddy fields (Thai Junior encyclopaedia project, 2018). During 2001 to 2011 the demand for Cassava from domestic use and exports increased, also during 2008/09, the demand for Cassava for Ethanol production increased. The market price of Cassava has fluctuated so the government launched the policy to subsidise the farmers by the Cassava Insurance project since 2000 (except 2008/09 the subsidy was the Cassava Mortgage project). During 2009/10 the area of Cassava declined because of a serious pest problem in Thailand so that the farmers lost their yield and changed to other crops. Since 2012, the demand of Cassava for export has continuously increased (Thailand Development Research Institute, 2012).

Cassava can be planted any time of the year but has two main planting times the first being from March and May, and the second time being November. Cassava takes approximately 8-16 months to reach the harvesting time (Thai Tapioca Development Institute, 2009).

Sugarcane:

In 1937, the first sugar factory was built in Thailand. In 1964, the first sugar factory was built near the study areas (in Buriram province) resulting in some land which is unsuitable for rice changing to sugarcane (Buriram Sugar Public Company, 2018). Currently three sugar factories are located near the study areas (Buriram and Surin provinces). Expansion of the area of sugarcane is due to the attractive market price and relates to the contract farming conditions (such as fertilizers, loans and knowledge) which are provided by the factory companies (Bank of Thailand, 2017 and Buriram Sugar Public Company, 2018).

For Sugarcane, once the plants are established, a stand can be harvested approximately 2-3 times (or 2-3 years) after the first harvest (once per year) but following the second harvesting year it gives declining yields, thus the farmers tend to replant new sugarcane. Most farmers in the North-eastern region plant the new Sugarcane between October and November, while the harvest time is between December and April (Usaborisut, 2018).

Eucalyptus:

Eucalyptus planting in Thailand has occurred since the 1950's, but in the north-eastern part of Thailand it has been promoted since 1985. Eucalyptus can be grown in areas where the conditions include saline soil and very dry soil that can also withstand flooding. The eucalyptus plantations were established to supply the Thai Pulp and Paper Company.

In 1994, the Thai government wished to promote Eucalyptus so as to compensate for the reduction of income compared to crops such as cassava by providing a subsidy in form of a soft loan as an incentive to the farmers to change to eucalyptus. Eucalyptus can be harvested after approximately 4-5 years (Forestry Department, 2013).

3.3 Land use (change) situation in the study areas

An assessment of land use change can be made from the land use maps for 2007, 2012, and 2016 in MCSW and 2006, 2011, and 2015 in LMSW from the Land Development Department of Thailand (data at 1:25,000 scale). The land use map can be used to understand the current land use and the types of changes and transitions which have occurred.

The land use classification in Thailand is based on the Land Use Classification System for use with remote-sensor data from the Ministry of Agriculture, USA. Land use has been classified by a hierarchical classification system (Chutirattanaphan, 2011). The land use map of Thailand was developed by the Land Development Department (under the authority of the Minister of Agriculture and Cooperatives). It has been created using a combination of satellite, aerial-photos and fieldwork surveys. The digital land use mapping began in 2000. The land use map for 2000/01 (1:50,000) was digitised from topographic maps and interpreted from LandSat5 TM satellite images. Subsequently, the land use map for 2006/07 (1:25,000) was created from aerial-photos, LandSat5 TM, and SPOT-5 imagery. Since 2008, land use maps (1:25,000) have been provided from the Thaichote (Panchromatic (2 m) and multispectral (15 m) imagery). Within the land use map there are three levels of classification. The level one classification consists of forest, agricultural, urban, waterbody and miscellaneous. For level two, the agricultural class consists of paddy field, field crops, perennial crops, orchards, horticulture, shifting cultivation, pasture and farmhouse, aquatic plants, aquaculture land, and integrated farm. The accuracy of land use mapping at level two was approximately 90-96% (varying between provinces) (Land Development Department, 2020). The level three distinguishes between individual crops. The classification used in this study is based on the level three classification, but with some aggregation of categories. While not explicitly calculated, level three land use mapping incorporates field survey/ ground truthing and the accuracy can be expected to be equally as good as level two.

Land use data for each study area were collected in the same way but are for different years because the watersheds were surveyed at different points in the national update cycle. The frequency of land use data updates for Thailand is now once every two years, though previously it was every four years (i.e. 2006/07, 2011/12, and 2015/2016).

Consequently, land use data for MCSW and LMSW are for slightly different years: MCSW has data from 2007, 2012 and 2016, while LMSW it is 2006, 2011 and 2015. The official land use year is based on the updating year (Chutirattanaphan, 2011; Land Development Department, 2020).

Land use was categorised into nine classes for each study areas based on sorting the classes from the highest to the lowest amount. The small amount of remaining agricultural land was grouped into Other Agricultural.

The nine land use categories for MCSW are: 1) Forest, 2) Urban, 3) Miscellaneous, 4) Rice, 5) Maize, 6) Pineapple, 7) Coffee and Tea, 8) Rubber, and 9) Other Agricultural for MCSW. For LMSW they are: 1) Forest, 2) Urban, 3) Miscellaneous, 4) Rice. 5) Sugarcane, 6) Cassava, 7) Rubber, 8) Eucalyptus, and 9) Other Agricultural.

The Other Agricultural category includes various small-scale crops, together with pasture. There are differences in the Other Agricultural category in the two study areas. In MCSW this category included lychee, longan, orange, cassava, oil palm, and vegetables, while in LMSW it included maize, oil palm, pasture, mango, longan, mulberry, banana, and vegetables.

The Miscellaneous category in both areas is combination of different uses which include waterbodies, rangelands, marsh and swamp, mine and pits, rubbish dumps and vacant areas. Table 3.2 illustrates the land use categories in MCSW and Table 3.3 those for LMSW.

Table 3.2 Land use categories in MCSW (Urban and Agricultural land use categories)

Urban villages, institutional, transportation and commination, industrial and other built-up	**Rice** (*Oryza sativa*)
	
Maize (*Zea mays*)	**Pineapple** (*Ananas comosus*)
	
Coffee (*Coffea*)	**Tea** *(Camellia sinensis)*
	
Rubber *(Hevea brasiliensis*)	**Other Agricultural** banana, orange, mango, lychee, longan, and cassava etc.
	

Table 3.3 Land use categories of LMSW (Urban and Agricultural land use categories)

Urban villages, institutional, transportation and commination, industrial and other built-up	**Rice** (*Oryza sativa*)
	
Sugarcane (*Saccharum offcinarum*)	**Cassava** (*Manihot esculenta*)
	
Eucalyptus *(Eucalyptus camaldulensis)*	**Rubber** *(Hevea brasiliensis*)
	
Other Agricultural banana, mango, mixed orchard, palm, maize, vegetables and pasture, etc	
	

3.3.1 Land use change in Mae Chan Sub-watershed

This section describes the historical and recent status of land use in MCSW. Tables 3.4-3.5 shows the extent of each land use in 2007, 2012 and 2016. Table 3.4 shows the land use categories which were used in this study and shows how the extent of each category has changed between from 2007 to 2016. The cross tabulation in Table 3.5 shows the change between individual categories. The land use in 2016 is indicated in the bottom row. Reading down the column indicates the previous use of the land in each category. The situation of the land use in 2007 is shown in the final column. Reading across the row indicates the transitions which have occurred within each category. Figure 3.9 shows the changes between specific pairs of land uses. It highlights the largest transitions in each time period (from 2007 to 2012 and from 2006 to 2011).

Table 3.4 Land use change between 2007, 2012 and 2016 in MCSW

Land use	Area (hectares)			Area (%)		
	2007	2012	2016	2007	2012	2016
Forest	65,813	54,479	49,424	52.33	43.31	39.30
Urban	4,890	5,947	6,218	3.89	4.73	4.94
Miscellaneous	4,829	5,250	5,190	3.84	4.17	4.13
Rice	18,448	18,410	20,162	14.67	14.64	16.03
Maize	10,497	21,707	23,270	8.35	17.26	18.50
Pineapple	722	2,319	2,778	0.57	1.84	2.21
Coffee and Tea	751	4,390	4,486	0.60	3.49	3.57
Rubber	656	3,331	4,929	0.52	2.65	3.92
Other Agricultural	19,172	9,943	9,320	15.24	7.91	7.41
Total	**125,777**	**125,777**	**125,777**	**100**	**100**	**100**

Table 3.5 Land use change in MCSW between 2007 (row) and 2016 (column) in percentage based on land use maps overlaid in GIS

Land use		Land use 2016 FOR	URB	MIS	RIC	MAI	PIN	COF	RUB	OTH	Total 2007
Land use 2007	FOR	38.97	0.23	0.47	1.6	8.01	0.27	0.92	0.96	0.88	**52.33**
	URB	0.01	3.8	<0.01	0.01	0.01	<0.01	0.03	<0.01	0.02	**3.89**
	MIS	0.01	0.19	2.62	0.13	0.21	0.21	0.01	0.26	0.2	**3.84**
	RIC	<0.01	0.19	0.07	13.54	0.13	0.19	0.01	0.18	0.35	**14.67**
	MAI	0.07	0.22	0.39	0.23	4.31	0.64	0.51	1.1	0.87	**8.35**
	PIN	<0.01	<0.01	0.09	0.03	<0.01	0.31	0.03	0.07	0.04	**0.57**
	COF	0.01	0.02	<0.01	0.01	0.01	-	0.51	0.01	0.03	**0.6**
	RUB	<0.01	0.02	0.01	0.02	0.02	0.2	-	0.22	0.04	**0.52**
	OTH	0.22	0.27	0.46	0.46	5.79	0.39	1.55	1.13	4.97	**15.24**
Total 2016		**39.3**	**4.94**	**4.13**	**16.03**	**18.5**	**2.21**	**3.57**	**3.92**	**7.41**	**100**

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, MAI= Maize, PIN= Pineapple, COF=Coffee and Tea, RUB=Rubber, OTH=Other Agricultural)

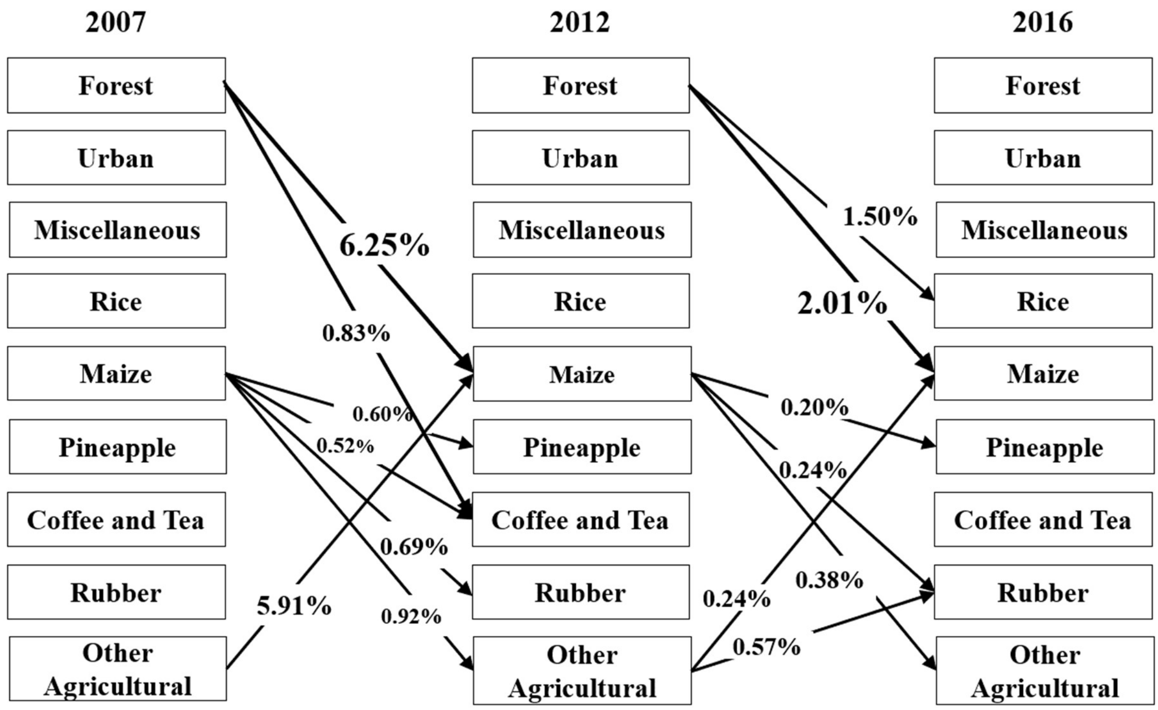


Figure 3.9 Transitions between major land use categories between 2007, 2012 and 2016 in MCSW

Looking at the land use change between 2007 and 2016 in MCSW (Table 3.4), the total area of Agricultural land (Rice, Maize, Pineapple, Coffee and Tea, and Rubber) except the Other Agricultural area increased, while Forest decreased. The area of Urban also increased during this period.

Forest was the most dominant land use in MCSW covering 52.33% of the area in 2007, which decreased to 43.31% in 2012 and 39.30% in 2016 (Table 3.4). By contrast, Maize increased from 8.35% in 2007 to 17.26% in 2012 and to 18.56% in 2016 while Rice was stable between 2007 and 2012, afterwards increasing from 14.64% in 2012 to 16.03% in 2016.

The main changes between 2007 and 2012 were conversion from Forest, Maize and Other Agricultural to other land use categories (Figure 3.9). The main transition from Forest was to Maize (6.25%) with a smaller transition to Coffee and Tea (0.83%). The main transition from Other Agricultural area was also to Maize (5.91%). At the same time, the main transitions from Maize were to Other Agricultural (0.92%), Rubber (0.69%), Pineapple (0.60%), and Coffee and Tea (0.52%).

Looking at the primary transitions between 2012 and 2016, the largest transitions between specific land use were from Forest, Maize, and Other Agricultural (which was the same as the main land use changes between 2007 and 2012) (Figure 3.9). The main area of Forest which was lost changed to Maize (2.01%) and Rice (1.50%). The largest conversion from Other Agricultural was to Rubber (0.57%) and Maize (0.24%), while the largest areas of Maize were allocated to Other Agricultural (0.38%), Rubber (0.24%) and Pineapple (0.20%).

Between 2007 and 2016, the largest allocation to Rice was from Forest (1.60%), while at the same time there was some transition from Rice to other crops (Table 3.5). An increase in the area of Rice is probably related to the government policy. In 2009/10, Thailand used the Rice Price Insurance Project, then in 2011/12 the policy changed to the Rice Mortgage Project that encouraged the farmers to continue to grow Rice and changed some non-Rice areas to Rice (see Section 3.2.3).

The area of Maize substantially increased between 2007 and 2012 by 8.91% of the total area. Between 2007 and 2016, the primary allocation to Maize was from Forest and from Other Agricultural while at the same time some of the existing Maize changed to other crops (Figure 3.9). Between 2012 and 2016 the area of Maize increased more slowly (by 1.24%) (Table 3.4). The reasons for the increase in Maize were discussed earlier in the chapter (see Section 3.2.3).

The area of Pineapple increased by 1.63% of the total area between 2007 and 2016. The largest areas of new Pineapple were allocated from Maize (0.64%) (Table 3.5). Between 2012 and 2016, the extent of Pineapple increased more slowly (by 0.36%).

The main transition in this period was from Rice to Pineapple (0.15%). The increase in the area of Pineapple was due to the attractive market price (see Section 3.2.3).

The area of Coffee and Tea increased substantially between 2007 and 2016 by 2.97% of the total area. The majority of the area of Coffee and Tea was allocated from Other Agricultural (1.55%) and Forest (0.92%) (Table 3.5). Between 2012 and 2016 the amount of Coffee and Tea was slightly increased (Table 3.4). The increase in the area of Coffee and Tea was due to the geography of the area and the attractive market price (see more detail in Section 3.2.3).

The area of Rubber substantially increased by 3.40% of the total area between 2007 and 2016. The most important transitions to Rubber were from Other Agricultural (1.13%) and Rice (1.10%) (Table 3.5). The increase in the area of Rubber related to government policy which promoted Rubber plantation (see Section 3.2.3).

Population growth, an increase in the number of tourists, and infrastructure development may have influenced increasing deforestation (to expand the area for food production and urbanisation). In the north of Thailand large scale traditional (shifting) cultivation by local (tribal) people has also been identified as an important cause of deforestation (Banijbatana, 1978; Germsak, 1992). The population growth rate of this area was approximately 2.50-8.20% between 2010 and 2015 (Department of Provincial Administration, 2017), the number of tourists has been increasing since 2012 as a result of the Government policy to promote tourist and logistic development in Chiang Rai province (Ministry of Tourism and Sports, 2017; National Statistical Office of Thailand, 2017). Also, the extension of roads to the border of Thailand has encouraged urbanisation (Office of the National Economic and Social Development Board, 2017). The area of Urban in MCSW increased from 2007 to 2016 (by 1.06%) (Table 3.4). New areas of Urban changed from all land use categories especially Forest and Maize (Table 3.5).

3.3.2 Land use change in Lam Mun Sub-watershed

Tables 3.6-3.7 show the changes which occurred between 2006 and 2015 in LMSW. The main transitions between the land use categories between 2006, 2011 and 2015 are shown in Figure 3.10.

Table 3.6 Land use change between 2006, 2011 and 2015 in LMSW

Land use	Areas (hectares)			Areas (%)		
	2006	2011	2015	2006	2011	2015
Forest	15,930	15,624	14,488	5.75	5.64	5.23
Urban	12,007	14,752	15,287	4.34	5.33	5.52
Miscellaneous	28,107	26,342	24,391	10.15	9.51	8.81
Rice	173,744	185,480	176,911	62.73	66.97	63.87
Sugarcane	6,140	6,294	9,991	2.22	2.27	3.61
Cassava	3,982	2,637	4,239	1.44	0.95	1.53
Rubber	2,817	6,715	14,315	1.02	2.42	5.17
Eucalyptus	15,324	16,507	15,549	5.53	5.96	5.61
Other Agricultural	18,925	2,623	1,805	6.83	0.95	0.65
Total	**276,975**	**276,975**	**276,975**	**100**	**100**	**100**

Table 3.7 Land use change in LMSW between 2006 (row) and 2015 (column) in percentage based on land use maps data analysis by GIS

Land use		Land use 2015									Total 2006
		FOR	URB	MIS	RIC	SUG	CAS	RUB	EUC	OTH	
Land use 2006	FOR	5.14	0.02	0.09	0.06	0.06	0.09	0.13	0.13	0.02	**5.75**
	URB	<0.01	4.28	0.01	0.03	<0.01	<0.01	<0.01	<0.01	<0.01	**4.34**
	MIS	0.03	0.07	8	0.8	0.05	0.06	0.11	1.01	0.02	**10.15**
	RIC	<0.01	0.15	0.29	58.46	1.98	0.23	1.09	0.47	0.07	**62.73**
	SUG	<0.01	0.02	0.02	0.02	0.84	0.24	0.96	0.1	0.03	**2.22**
	CAS	<0.01	<0.01	<0.01	0.02	0.23	0.31	0.77	0.09	0.01	**1.44**
	RUB	<0.01	<0.01	<0.01	<0.01	0.03	0.02	0.93	0.02	0.01	**1.02**
	EUC	0.03	0.02	0.26	0.12	0.09	0.39	0.94	3.63	0.06	**5.53**
	OTH	0.03	0.96	0.13	4.36	0.32	0.2	0.24	0.17	0.43	**6.83**
Total 2015		**5.23**	**5.52**	**8.81**	**63.87**	**3.61**	**1.53**	**5.17**	**5.61**	**0.65**	**100**

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, SUG= Sugarcane, CAS=Cassava, RUB=Rubber, EUC=Eucalyptus, OTH=Other Agricultural)

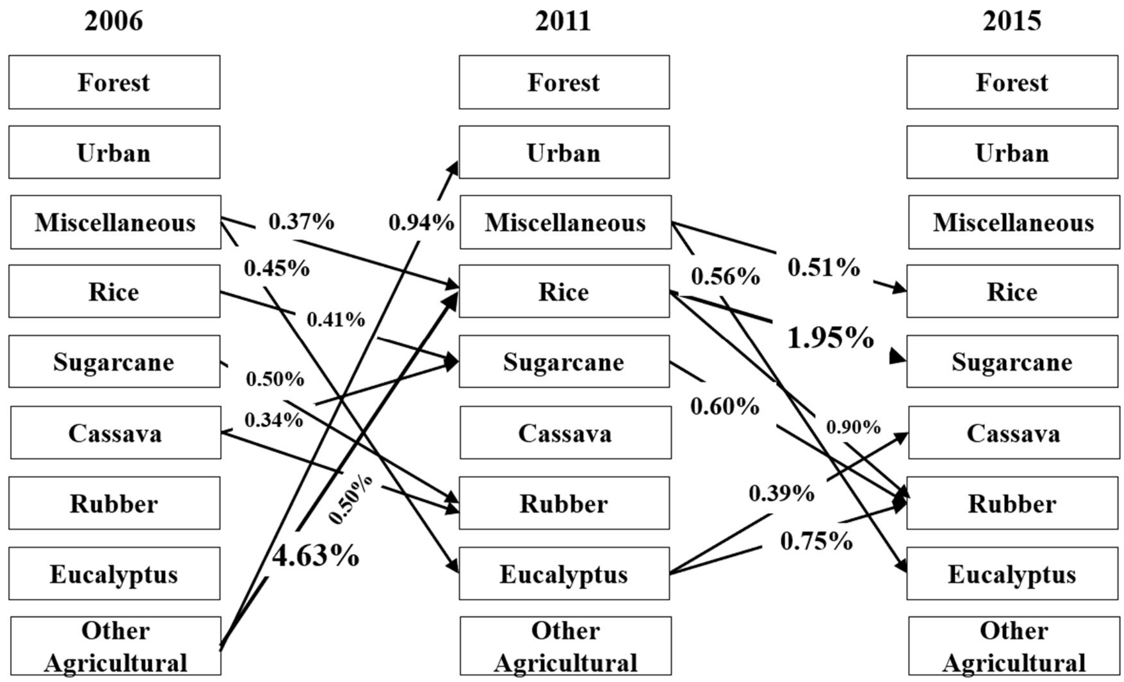


Figure 3.10 Transitions between major land use categories between 2006, 2011 and 2015 in LMSW

Looking at the trends between 2006 and 2015 in LMSW (Table 3.6), the amount of Rice, Cassava and Eucalyptus fluctuated. At the same time, the area of Urban, Sugarcane and Rubber increased while Forest, Other Agricultural and Miscellaneous decreased.

Rice is a dominant land use within LMSW which takes up approximately 60% of the area. Between 2006 and 2015, the area of Rice increased to 66.97% in 2011 then dropped to 63.87% in 2015 (Table 3.6). The increase in Rice was probably related to the favorable government policy at the time which provided a subsidy via a price guarantee which encouraged the expansion of this crop. This produced a huge shift from Other Agricultural to Rice (Figure 3.10). The government policy was subsequently amended, and this is likely to account for subsequent reduction in the area of Rice.

The large increases in the area of Rubber can also be attributed to the government policy which promoted Rubber plantations. The favourable market price for rubber at this time also attracted the farmer’s interests. Rubber was particularly promoted for land which is less suitable for other crops. It can be seen that some of the land which was previously used for Eucalyptus has transitioned to Rubber. Eucalyptus was previously planted to supply local paper factories, but this crop has ceased to become important economically. Rubber can provide an income over the long term and it is therefore seen as a useful crop to generate a sustainable income and combat poverty.

The area of Sugarcane in this study area has increased substantially in recent years. As with other areas in the north-eastern region of Thailand the suitability for Rice can be more marginal due to factors such as saline soil or drought. Sugarcane is a good alternative for some parts of the area which are not particularly suitable for Rice plantation. The government also promotes farmers to change from Rice to other crops such as Sugarcane or Cassava to diversify their income and provide additional choices. The attractive market price can also encourage farmers to cultivate this crop. A relatively large increase in Sugarcane can be seen following the end of the Rice subsidy scheme. When the true market prices are applied some of the farmers appear to choose Sugarcane for a part of their land, as the price of Sugarcane is more stable and attractive.

3.4 Summary

The first section of this chapter focused on research design and methodologies. The main research methodology consisted of four stages which were (input) data collection, the calibration, validation, and simulation. The chapter then described the selected land use modelling software packages for the prediction and simulation of the future land use in this study. The selected (model) software for this study were Dyna-CLUE, CA-Markov module, MCE module, and LCM module in IDRISI TerrSet and NetLogo. The input data for all models was identical in many respects, only for the ABM was the additional data from fieldwork (farmer and land use expert interviews) different.

In order to investigate the land use change models and reflect on the performance of the models it is necessary to consider the characteristics of the selected study areas. The chosen study areas are located in Thailand. They consist of Mae Chan Sub-watershed (MCSW) which is located in the Northern region, and Lam Mun Sub-watershed (LMSW) which is located in the North-eastern region. Mae Chan Sub-watershed is a rice-growing area and is therefore a good choice to represent the wider North-Eastern region (which produces 60% of the Rice in Thailand). Mae Chan Sub-watershed on the other hand features different upland crops and is therefore somewhat representative of the mountainous areas within Thailand. The researcher also had personal experience of the areas and local contacts which were helpful to understand the local land use issues in more detail.

The population density of LMSW is higher than MCSW. Both areas have a high capacity for food production from crops such as rice, maize, pineapple and coffee and tea in MCSW, and rice, sugarcane, and cassava in LMSW. Both study areas are different from each other for example in the size of area, climate and temperature, topography, and the main crops. Selecting two contrasting study areas potentially allows broader conclusions to be made (e.g. the model performed well in these circumstances, but not in these etc.).

The third section of this chapter highlights the land use change situation in the study areas. Agricultural land in MCSW (between 2007, 2012 and 2016) and LMSW (between 2006, 2011, and 2015) increased in its total area, while Forest declined.

In MCSW, Forest is a dominant land use category that covered more than half of the total area in 2007. In 2016 it was still the most extensive individual land use in the sub-watershed. Between 2006 and 2015, the main changes were from Forest to Maize, from Other Agricultural to Maize, and from Maize to Coffee and Tea.

In LMSW, Rice is the main land use, covering more than 60% of the total area. Between 2006 and 2015, the key changes were from Rice to Sugarcane, from Rice to Rubber and from Other Agricultural to Rice. The land use change which took place in MCSW included, not only deforestation, but also infrastructure expansion, while in LMSW the changes were driven by government policy and the agricultural markets.

The model calibration and validation results are presented in Chapters 4 and 5.

Chapter 4 | Set-up and calibration

This chapter describes the stages involved in setup and calibration of Dyna-CLUE, IDRISI, TerrSet tools (CA-Markov module, the Land Change Modeller (LCM) module and the Multi-Criteria Evaluation (MCE) module), and NetLogo (Agent-based model). It explains how the spatial information about land use change, the characteristics of the study area, and the driving factors can be established. The parameter set-up section explains the input data and the methodology for each of the models (Section 4.1).

4.1 Model parameter set-up

The models in both study areas (MCSW and LMSW) were calibrated over a five-year period, 2007 to 2012 for MCSW and 2006 to 2011 for LMSW.

In order to quantify observed land use change, the first step was to obtain the map of the land cover for the calibration years. The original maps distinguished over twenty land use categories which were aggregated into nine categories for MCSW; 1) Forest, 2) Urban, 3) Miscellaneous, 4) Rice, 5) Maize, 6) Pineapple, 7) Coffee and Tea, 8) Rubber and 9) Other Agricultural. The land uses in LMSW were also aggregated into nine categories; 1) Forest, 2) Urban, 3) Miscellaneous, 4) Rice, 5) Sugarcane, 6) Cassava, 7) Rubber, 8) Eucalyptus and 9) Other Agricultural (see Section 3.1 of Chapter 3). These were used as the dependent variables for the prediction of land use change.

The independent or explanatory variables were selected based on the available data and the ability to express the data as a spatially explicit variable. Nine factors were chosen to analyse the allocation of land use in this study. The type and range of the factors is shown in Table 4.1 for MCSW and LMSW. The driving factor maps were prepared from the collected data (from Table 4.1) as shown in Table 4.2.

Table 4.1 Land use and driving factors evaluated for MCSW and LMSW

Factors	Type of factor	Unit	Min-Max	
			MCSW	LMSW
Soil fertility	Ordinal	n/a	low-medium	low-medium
Soil drainage	Ordinal	n/a	poor-well	poor-well
Slope	Continuous	degree	0 - 61	0 – 32
Annual rainfall	Continuous	mm./year	1,522 – 1,664	1,024 – 1,351
Distance to roads	Continuous	km.	0 - 6.05	0 – 2.70
Distance to rivers	Continuous	km.	0 - 7.35	0 - 9.53
Distance to agricultural markets	Continuous	km.	0 - 46.39	0 – 37.07
Land right	Dichotomous	n/a	right/no right	right/no right
Population density	Continuous	person/ha	0.73-3.15	0.49 -3.16

Table 4.2 Driving factor map data

Criteria	Criteria source data	Descriptions
Soil fertility	Soil map	Soil fertility capacity
Soil drainage	Soil map	Soil drainage capacity
Slope	DEM	Slope extraction
Annual rainfall	Climatological data	Spatial interpolation
Distance to roads	Road map	Euclidean distances
Distance to rivers	Stream map	Euclidean distances
Distance to agricultural markets	Land use maps	Euclidean distances
Land Right	Forest map Agricultural land reform map Interview data	Data extraction and reclassify
Population density	Administration boundary map Population statistics	Population density calculated between the amount of population in subdistrict and the area of each subdistrict

Researchers use different cell sizes in their studies, often related to the different conditions and extents of the study areas, or to the purposes of the study. For this study it was necessary to use a cell size which could adequately represent different agricultural land uses (on a field level). The land use data (and the other data sets) were converted from vector to raster format at a resolution of 250×250m grid cells. A coarser cell size would have resulted in a loss of accuracy (maybe missing smaller land uses altogether). A 250m cell resolution was judged to create a reasonably accurate representation of the land uses in the study areas, whilst also being feasible for computational purposes. Experiments were conducted with a finer resolution, but it was concluded that little benefit was gained in terms of land use representation and problems were experienced in running some models. It was considered important for comparison purpose to have the same resolution for each model. This use of 250×250m cells is consistent with regional-extent land use change modelling in Canada (Pouliot et al., 2013) and in Africa (Vancutsem et al., 2013).

All of the data (including that originally in vector format at scale 1:25,000) were converted to 250 m resolution raster grids (rasterization) using maximum area criteria in GIS software, i.e., the feature with the largest area of land in the cell determines the attribute assigned to that cell. It should be noted that when the 1:25,000 land use maps were converted to a 250×250m cell resolution there was inevitably some generalisation. As the example in Figure 4.1 shows, using a maximum area condition means that only the intersecting feature with the largest area is represented in the output.

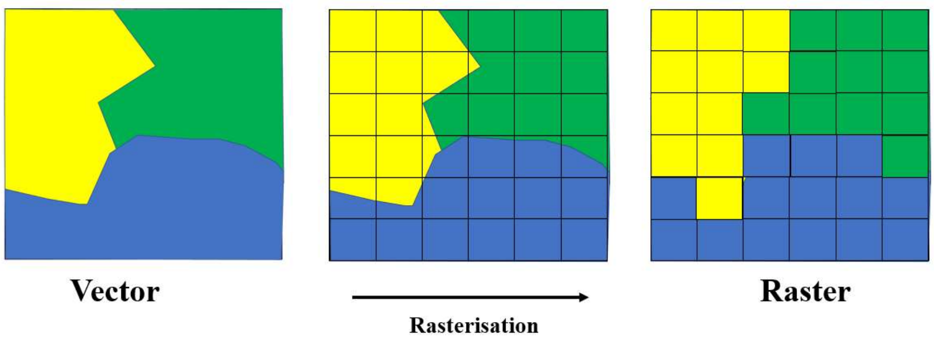


Figure 4.1 Rasterisation using a maximum area condition

Figures 4.2 and 4.3 show the spatial distribution of driving factors for MCSW and MCSW. The soil fertility and drainage data were extracted from soil maps. Soil fertility and drainage influence nutrient supply and the ability to grow specific crops as crops need nutrients and water from the soil. Soil fertility is classified as low, medium or high fertility, whilst the fertility of both study areas was low or medium (Figures 4.2 and 4.3). Soil drainage is classified as very poor, poorly, somewhat poorly, moderately well, well, or excessively drained, whilst the drainage of both study areas was classified as poorly, somewhat poorly, moderately well, or well drained.

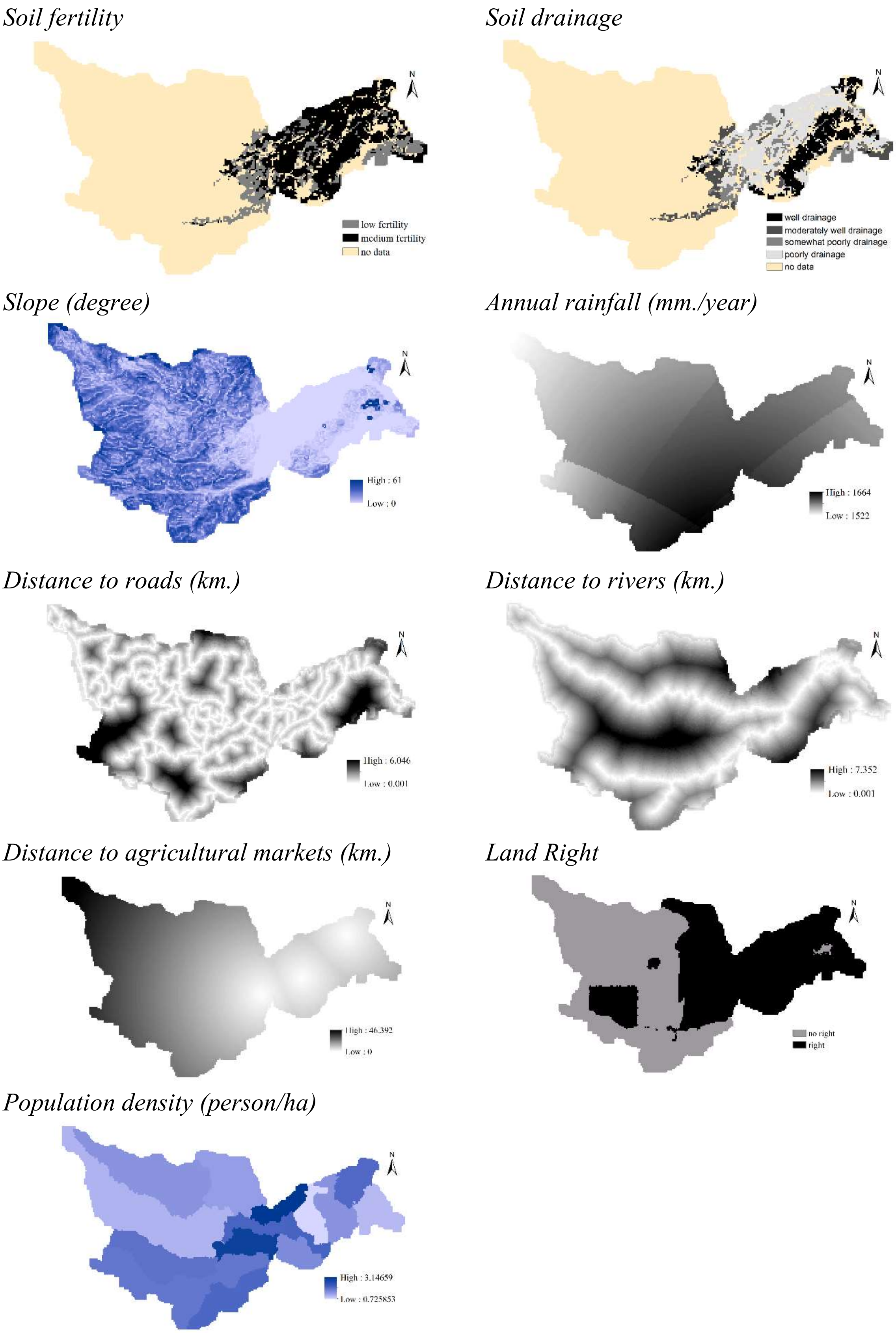


Figure 4.2 The spatial distribution of driving factors for MCSW

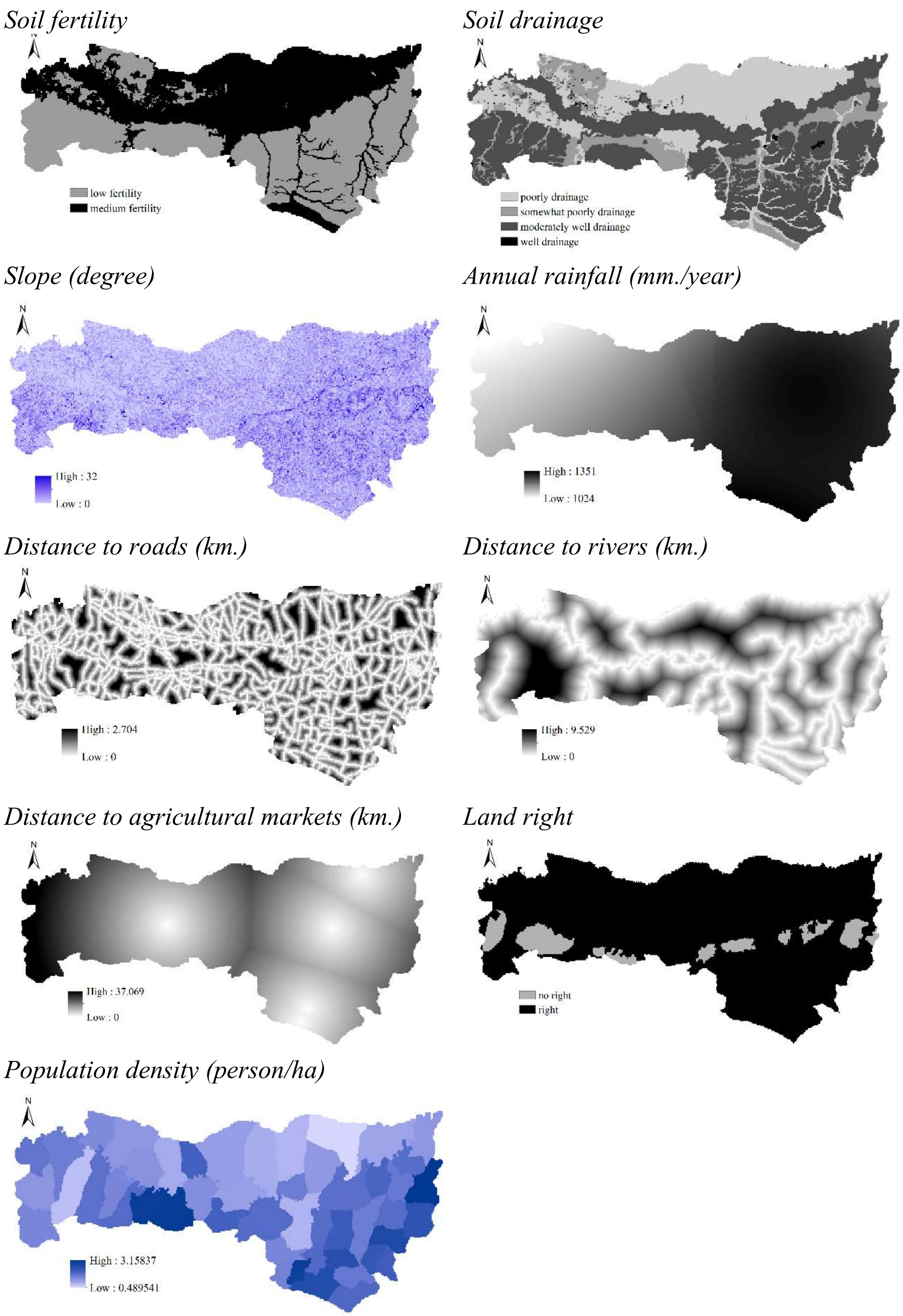


Figure 4.3 The spatial distribution of driving factors for LMSW

Looking at the spatial distribution for soil fertility and soil drainage in MCSW (Figure 4.2), there is an area of no data. In these areas the soil groups and slope are complex and most of the area is Forest, so no survey of the finer detail of soil fertility and soil drainage has been undertaken. Most of this area in MCSW is Forest, as discussed in Section 3.3 of Chapter 3.

The slope was extracted from the DEM (Digital Elevation Model) (Section 3.1.2 of Chapter 3). The slope in MCSW (Table 4.1 and Figure 4.2) shows (much) more variation than in LMSW (Table 4.1 and Figure 4.3). The annual rainfall map was generated using a spatial interpolation (Inverse Distance Weight) technique in ArcMap to estimate cell values by averaging those from gauge-station points with climatological data for a period of 30 years.

Partly due to some missing data, soil fertility and soil drainage were not added to the regression model for Forest, while soil fertility and annual rainfall were not added to the regression model for Urban. Most of the areas of Forest and Urban do not have any soil fertility data so no statistical relationship can be evaluated. However, while soil fertility and annual rainfall are important factors for agriculture, they do not affect the suitability of locations for Urban development. Consequently, the absence of data on these factors for parts of the study region is not a problem for the modelling.

The distance to roads was computed from the roads map while the distance to agricultural markets was derived and calculated from the land use map. The distance to roads and to agricultural markets can be used to help understand the cost of transporting agricultural commodities. The distance to rivers was computed from the rivers map. This data can be used to help predict the availability of irrigation during the dry season. The distance to roads, rivers and markets are Euclidean distances which were generated using ArcMap.

The land rights which were distinguished in this study are: where the landowners have a right and where they have no right to do their farming (the farmers or the landowners have evidence of ownership). The land tenure is derived from the Forest zone (where there is no right) and data from the interviews. In terms of completeness, Figures 4.2 and Figure 4.3 show the land right map is dichotomous which could have an important influence on the modelling results. Population density was calculated using demographic statistics and the area boundaries.

All models had the same input data for parametrising, such as the land use maps and the variable factors map. Dyna-CLUE has four main scenario conditions (land requirements, spatial policies, land use specific conversion settings and location characteristics), as well as the interpretation of the relationship between driving forces and land use change using logistic regression (see Section 4.2). The first step of the CA-Markov, MCE and LCM modules is to prepare the Markov Chain matrices, and then the next step is to combine with the Cellular Automata method. MCE and LCM use the driving factors for the potential transition for the calibration process (see Section 4.3). Finally, for the ABM model set up the agent, the interaction between agents, and the environment of ABM need to be prepared as the input data for the model (see Section 4.4).

4.2 Dyna-CLUE

The Dyna-CLUE model was developed to simulate land use change using an empirical-statistical approach (see more description in Chapter 2). The model has a number of parameters that need to be specified before the simulation can be started. The overall process is summarized in Figure 4.4 and the parameter settings depend on the assumptions provided for a particular scenario. There are four different scenario conditions (or types of Dyna-CLUE data) that are required; Land requirements, Spatial policies (area restrictions), Land use specific conversion settings and Location characteristics (Verburg and Overmars, 2009). In addition, Dyna-CLUE uses a statistical analysis to define the relations between the land use location and the specific factors, such as soil fertility, slope, accessibility etc. (Mas et al., 2014; Trisurat et al., 2019).

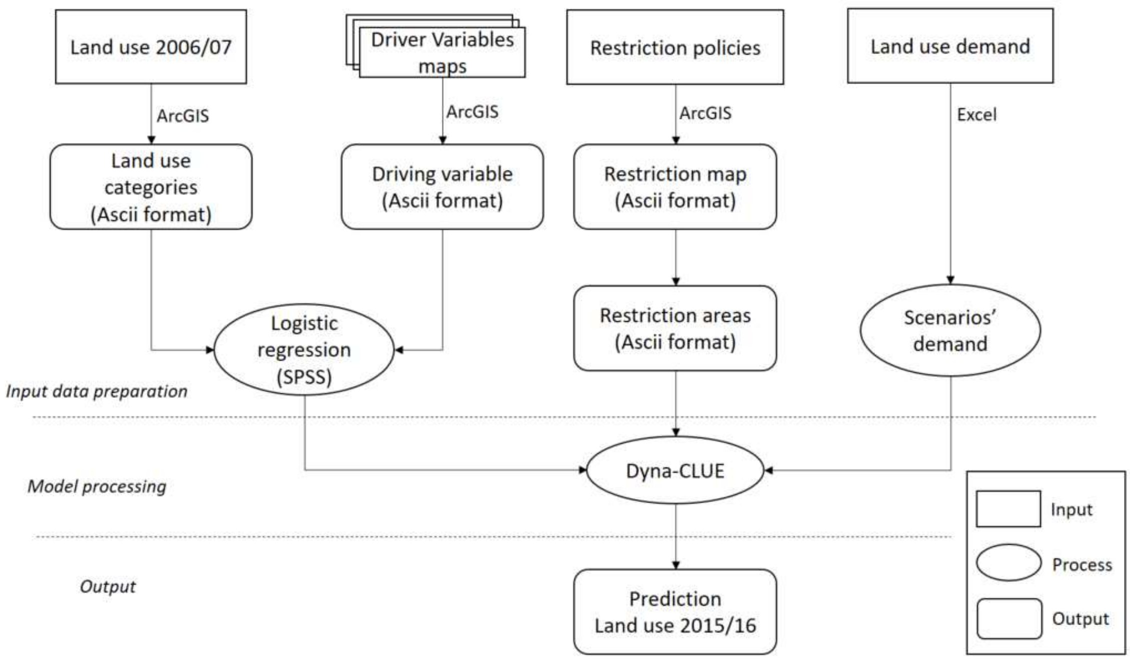


Figure 4.4 Dyna-CLUE method to predict land use change

4.2.1 Land requirements

The land use requirement, or land demand, is set for each land use in each year, in the demand file. The land demand sets the total amount of each land use. The first part of the demand relates to the number of years in the scenario. The second part of the demand translates these demands into land use types at different locations within the study region. The trends of land use change observed in the past and projected into the near future is a common technique to calculate land use requirements in the scenario (this is known as the trend scenario) (Verburg and Overmars, 2009; Trisurat et al., 2010; Tizora et al., 2018).

In this model, the land use requirement assumed the transformation rates of the past from 2006 to 2015 for LMSW and 2007 to 2016 for MCSW will continue in the future to 2025. The demand unit was specified in hectares.

4.2.2 Spatial policies (area restrictions)

The area restriction or spatial policies area defines where land use change is restricted through spatial land use policies (Verburg and Overmars, 2009; Trisurat et al., 2010). In other words, this area indicates where land use change is restricted for some reason. No spatial policy or area restrictions were implemented in the model. The Forest area in Thailand is protected by law. However, it can be seen from the observed data that some areas of Forest have been converted to crops. These land use changes are possibly encroachments into the protected area. For this study the area restrictions setting is “no restrictions”. This setting was chosen because, in reality, there has been some encroachment into the protected area.

4.2.3 Land use type specific conversion setting

The conversion elasticity determines the temporal dynamics of the model simulation. The parameter sets are conversion elasticity and land use transition sequences. Conversion elasticity is set for each land use type and relates to the ease with which each land use type can change (Verburg and Overmars, 2009; Trisurat et al., 2010). The possible elasticity of conversion for nine land uses was indicated in Table 4.3, where the range of change is from “0” meaning easy to change to “1” meaning most difficult to change. The elasticity conversion numbers were the average results from discussions with three land use experts in Thailand (Section 3.1.3).

Table 4.3 The conversion elasticities for the two sub-watersheds

Mae Chan Sub-watershed		**Lam Mun Sub-watershed**	
Land use categories	**Conversion elasticity**	**Land use categories**	**Conversion elasticity**
Forest (FOR)	1	Forest (FOR)	1
Urban area (URB)	1	Urban area (URB)	1
Miscellaneous (MIS)	0.4	Miscellaneous (MIS)	0.4
Rice (RIC)	0.5	Rice (RIC)	0.5
Maize (MAI)	0.3	Sugarcane (SUG)	0.3
Pineapple (PIN)	0.3	Cassava (CAS)	0.3
Coffee and Tea (COF)	0.5	Eucalyptus (EUC)	0.5
Rubber (RUB)	0.7	Rubber (RUB)	0.7
Other Agricultural (OTH)	0.4	Other Agricultural (OTH)	0.4

The conversion elasticity can vary between different locations depending on the government policy and which crop is considered important and is promoted to the market.

The next set of input files were the conversion matrix and the land use transition sequences, which set the allowable conversion and change from one category to another category. This was done in a land use conversion matrix. Some land use changes may not be possible (Urban cannot become Rice for example), and other land use conversions are unlikely. The number in the matrix defined which land use types the present land use can be converted to (i.e. if the conversion is allowed to occur or not).

The land use conversions are specified in a land use conversion matrix. This specifies the possible conversions between nine land use, where “0” stand for impossible change and “1” indicates possible to change.

4.2.4 Location characteristic

Dyna-CLUE assigns land use change using the location preferences of the specific land use type. The location preference reflects the relationship between the driving factors and the land use types of the specific area, with a probability function drawn from logistic regression analysis (Verburg and Overmars, 2009; Trisurat et al., 2010; Tizora et al., 2018). In other words, the variable factors affect the land use allocation. This input requires results of logistic regression equations in text file format.

The logistic regression analyses are calculated with the statistical software SPSS. Logistic regressions were conducted from the land use map for 2006 (for LMSW) and 2007 (for MCSW) to examine the relationship between land use types and a range of factors (see Tables 4.1 and 4.2). Land use types were set as the dependent variables, while the environmental factors were set as the independent variables. The logistic regression generates the coefficient to predict a logit transformation of the probability of land use types of interest. This was used to select the relevant factors from a set of location characteristics by the stepwise regression procedure. In this process, each variable is added individually to the model, starting with the strongest predictor and the variables added in the previous steps are retested to see if they are significant. If they are significant, they were added. The stepwise approach removes insignificant variables from the logit regression (Rogerson, 2015).

The logistic model is presented as follows:

$$\text{Logit}(p) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \ldots + b_kX_k$$

Where p is the probability of land use type occurring within a particular grid cell,

b_0 is the constant obtained from the logistic regression model,

b_k is the coefficient of driving factors estimated through the logistic regression model, and

X_k is the location factor affecting the land use suitability (k)

A logistic regression analysis was carried out for each land use category, which resulted in nine regression models per watershed. The analyses used a 95% confidence level, which was chosen because it is the generally accepted standard and has been widely adopted (e.g. Verburg and Overmars, 2009). The insignificant variables were excluded though the stepwise regression procedure. The probability level of entry in the model was 0.01, and the probability level for removing the variable was set at 0.02.

The Receiver Operating Characteristic (ROC) value, which is the goodness of fit measurement of the logistic regression model, is conceptually similar to the R^2 statistic in Ordinary Least Square regression (Tables 4.4 and 4.5). A completely random fit model gives a ROC value of 0.5, where-as a perfect fit result gives a value of 1.0 (Verburg and Overmars, 2009).

Tables 4.4 and 4.5 present the coefficients, which were derived from the logistic regression and also indicates which are the significant factors for each land use type.

Table 4.4 The calculated of values of the logistic regression and the ROC result of the location characteristic of MCSW

Factors	**Forest**	**Urban**	**Miscellaneous**	**Rice**	**Maize**	**Pineapple**	**Coffee and Tea**	**Rubber**	**Other Agricultural**
Soil fertility	=	=	-	2.582 ^{1}	-0.399 ^{6}	-1.492 ^{4}	-1.127 ^{1}	-0.847 ^{4}	-0.701 ^{3}
Soil drainage	=	-1.060 ^{2}	-0.209 ^{4}	-0.722 ^{2}	0.705 ^{1}	2.093 ^{1}	-	1.153 ^{1}	0.517 ^{2}
Slope	0.116 ^{1}	-0.137 ^{3}	-	-0.208 ^{3}	-	-	-	-	-0.011 ^{6}
Annual rainfall	0.026 ^{5}	=	-0.032 ^{3}	0.007 ^{6}	0.008 ^{5}	-	-0.020 ^{4}	-0.057 ^{2}	-
Distance to road	0.232 ^{3}	-0.850 ^{4}	0.864 ^{2}	-	-0.415 ^{4}	-	-0.558 ^{2}	-	-
Distance to river	0.083 ^{7}	-0.309 ^{5}	-	-0.213 ^{5}	0.192 ^{3}	0.320 ^{6}	0.277 ^{3}	-	0.065 ^{5}
Distance to agricultural market	0.096 ^{4}	-0.031 ^{7}	-0.241 ^{1}	-	0.057 ^{2}	-0.672 ^{3}	-	-0.098 ^{3}	0.058 ^{1}
Land right	-0.267 ^{2}	1.113 ^{1}	0.464 ^{6}	0.990 ^{4}	-0.266 ^{7}	-2.254 ^{5}	0.798 ^{5}	-	0.300 ^{4}
Population density	-0.458 ^{6}	0.552 ^{6}	-0.366 ^{5}	-	-	1.072 ^{2}	-	0.468 ^{5}	-
Constant	-43.464	-1.604	50.683	-13.443	-16.647	-7.529	26.181	85.1	-3.115
ROC	**0.813**	**0.811**	**0.881**	**0.939**	**0.711**	**0.981**	**0.748**	**0.910**	**0.654**

all variables significant at $p<0.05$, ‘=’ not added in the regression model, ‘-‘ insignificant value, and “ $^{1,2,3,\ldots,9}$ “ the variables enter on step

Table 4.5 The calculated of values of the logistic regression and the ROC result of the location characteristic of LMSW

Factors	**Forest**	**Urban**	**Miscellaneous**	**Rice**	**Sugarcane**	**Cassava**	**Rubber**	**Eucalyptus**	**Other Agricultural**
Soil fertility	=	=	-	-0.786 [4]	-3.877 [3]	-2.459 [2]	-3.133 [4]	1.401 [2]	-
Soil drainage	=	0.226 [5]	0.503 [2]	-0.954 [3]	0.961 [7]	0.899 [5]	1.763 [2]	1.915 [1]	-0.493 [2]
Slope	0.034 [6]	0.037 [7]	0.060 [7]	-0.124 [5]	-	0.054 [7]	-	0.055 [7]	-
Annual rainfall	0.014 [2]	=	-0.063 [5]	0.066 [2]	-0.014 [4]	-0.012 [3]	-0.012 [3]	-0.004 [3]	-0.015 [1]
Distance to road	-0.824 [4]	-1.579 [1]	0.626 [4]	-0.189 [8]	0.957 [6]	0.731 [6]	0.715 [5]	0.474 [5]	-0.314 [6]
Distance to river	-0.082 [5]	-0.135 [3]	-0.873 [1]	-0.033 [9]	0.201 [1]	0.383 [1]	0.396 [1]	0.083 [6]	0.232 [3]
Distance to agricultural market	0.080 [3]	-0.026 [4]	-0.023 [6]	-0.013 [6]	0.030 [2]	-	-0.038 [6]	-	0.012 [7]
Land right	-4.158 [1]	0.645 [6]	-	2.824 [1]	-	-	-	-0.510 [4]	0.544 [4]
Population density	-	0.338 [2]	-0.562 [3]	-0.167 [7]	1.068 [5]	0.882 [4]	-	-	0.764 [4]
Coefficient	-18.150	-3.990	1.133	-4.925	10.113	6.773	5.120	-7.052	14.530
ROC	**0.861**	**0.691**	**0.799**	**0.820**	**0.930**	**0.936**	**0.939**	**0.838**	**0.859**

all variables significant at $p<0.05$, '=' not added in the regression model, '-' insignificant value, and " [1,2,3,…,9] " the variables enter on step

The ROC values for each of the land use categories in MCSW range from 0.654 to 0.981 and in LMSW range from 0.691 to 0.939. A ROC value of over 0.7 and less than 0.8 is acceptable, while a ROC value over 0.8 is excellent. These means the model is generally good, with the majority of the values being over 0.8. It can be concluded that the results of the logistic regression model are capable of explaining the spatial variation occurring in most of the different land use categories in this study (in the validation stage). However, Other Agricultural for MCSW, and Urban, for LMSW, showed a ROC value of less than 0.7. This value needs to be improved in the future by incorporating more accurate driving factors which have a stronger correlation with the land use categories. The lower accuracy may also indicate that the distribution of land use cannot be explained by environmental factors alone.

The next sub-section (Section 4.2.5) discusses the interpretation of the relationship between driving forces and land use change using logistic regression to understand this relationship in both study areas.

4.2.5 The interpretation of the relationship between driving forces and land use change by logistic regression

The results of the logistic regression models for each land use type in MCSW and LMSW are presented in Tables 4.4 and 4.5 (Section 4.2). Dyna-CLUE was applied to analyse the land use change which occurred between two dates. It can be seen that not all factors were included in the logistic regression and each factor contributed differently depending on the land use type.

The biophysical factors of this study consisted of soil fertility, soil drainage, slope, and annual rainfall. The socio-economic factors consisted of distance to road, distance to river, distance to agricultural market, land right and population density.

Mae Chan Sub-watershed (MCSW)

Biophysical factors: These refer to the impact of biophysical factors such as soil fertility, soil drainage, slope, and annual rainfall (Zhao et al., 2018). The first point to note is that increasing soil fertility is strongly identified with the presence of Rice (Hyandye et al., 2018; Zhao et al., 2018; Siagian et al., 2019b). Soil fertility has a negative relationship with other crops such as Maize, Pineapple, Coffee and Tea, and Rubber. Rice is important in Thailand as a traditional staple food and it is also the most important crop for export. In land use decision-making the farmers give priority to using their land as Rice before selecting to grow the other choices of crop. This could explain why high fertility is associated with the presence of Rice. As the high fertility land is occupied by Rice, other crops tend to be found on less fertile land (and not suitable for Rice). As a result, the distributions of these crops tend to be associated with lower fertility.

Secondly, areas with poor drainage are more likely to be Urban or Miscellaneous. The drainage characteristics are determined by the properties of the soil texture. Poorly drained areas are associated with silt-clay and clay soil. Poorly drained land is suitable for Rice. This is reflected in the logistic regression model, where poor drainage is associated with increasing probability of Rice. On the other hand, increasingly well drained land is associated with the presence of Maize, Pineapple, Rubber and Other Agricultural crops.

Thirdly, the slope characteristics clearly affect the distribution of Forest, Urban, Rice and Other Agricultural categories. Steep slopes have a high probability of being forest. The geography of this area is hilly, and slopes are often steeper than 5%. In addition, the specific characteristics of conservation land for forest in Thailand is identified with land where the slope is more than 35% (as well as land with complex slopes). These areas of forest are conserved by law. On the other hand, most of the existing built-up areas and cities are located in the plain area. This naturally results in a negative relationship between probability of Urban and slope. Similarly, the appropriate category of slope for paddy field is plain (slope 0-2%). This is concerned with the potential for mechanisation in the field (which would be impossible on steeper slopes). This naturally results in a negative relationship between probability of Rice and slope.

Rainfall appears in many of the models, but it is a weak predictor. Increasing annual rainfall values lead to a higher probability of Forest, Rice or Maize being present. Forest and rainfall are positively correlated by nature as Forest tends be in regions with a higher rainfall. Forest cover is more common within the mountains, and these areas also have higher rainfall, so it is natural that Forest would be correlated with higher rainfall. Most of the Maize area is near to Forest, that is, Maize is often grown in Forest clearings in the mountains. Maize is grown in a rainfed agricultural system that needs rainfall of about 300-800 mm in the growing period (Food and Agricultural Organization, 1976). Rainfall has a low effect on the distribution of Maize. There is a small positive correlation, which could be the result of Maize replacing Forest in high rainfall areas. For Rice also most of the paddy field irrigation comes from rainfed agriculture, which needs rainfall of about 800-2,000 mm per year. The farmers can collect water in their farm ponds. There is a small positive correlation between rainfall and Rice, but rainfall is not a strong predictor for Rice. In contrast, decreasing rainfall rates lead to increased probability of Coffee and Tea, and Rubber. These are perennial crops that have deeper roots and can use underground water. It is likely therefore that they might be found in drier areas, which are unsuitable for other crops.

The result of the regression analysis shows that all the environmental factors have some effect on the distribution of Rice. Fertility was found to be the most important factor. The probability of a cell being Rice increases with rising fertility (Zhao et al., 2018). For the other crops, only some of the environmental factors were found to be important.

Looking at Maize and Rubber, soil fertility had some effect on distribution, but soil drainage was the most important predictor for these crops. Maize and Rubber are more likely to be found on well-drained soil. This could be explained by the crop requirement and their water requirement. Rainfall also had some effect on distribution, but slope was not significant.

Of the biophysical variables, only soil fertility and soil drainage had an effect on the allocation of Pineapple, with soil drainage being more important than soil fertility. Changes in Coffee and Tea relate negatively with soil fertility and annual rainfall, but in this case soil fertility is the more important factor.

Socio-economic factors: Firstly, this refers to the impact of accessibility, which is defined by measures such as distance to road, distance to river, and distance to agricultural market. It can be seen that increasing distance to road, river and market are strongly identified with probability of Forest (Zhao et al., 2018; Trisurat et al., 2019). In contrast, all the accessibilities have a negative relationship with Urban. Roads and markets are characteristic features of Urban areas, and this could explain the negative relationship with these factors. Similarly, the Urban areas tend to be located near rivers. Areas that are near to the river have a high probability of being Urban or Rice. This relationship between Rice and distance to river reflects the opportunity to provide irrigation from the river. When the area is close to a river, the farmers can easily provide a water supply to their farm by the canals. The farmers give the priority to paddy fields in the areas which are near to the river, before they plan to select the other crops on their farm. Put differently, the areas with increasing distance to river are associated with a higher probability of the other crops being present. The exception to this is Rubber, which does not have any relationship with distance to road or river.

The distance to agricultural market had an effect on the allocation of Pineapple and Rubber, whereas for Rice, Coffee and Tea it was not significant. The method of selling the crops could help explain whether distance to market is important or not. In the case of Rice, the merchants buy the yield at the farmers' village and the farmers store the crop within their barn at the village. Thai farmers' barns are located at their house area. Similarly, Coffee and Tea are likely to be sold to a merchant and distance to market is not important.

Looking at land rights, land tenure is required not only for Urban (Krčílková and Janovská, 2016 and Schürmann et al., 2020), but also for crop areas, which require land where there is some kind of right (title deeds and agricultural land reform). The negative relationship between land tenure and Maize or Pineapple could occur where areas of Forest are converted to Maize or Pineapple, but there is no official right to the land.

Population density has a positive relationship with Urban, Pineapple and Rubber. All of these categories are more likely to occur in areas of higher population density. High population density is an obvious characteristic of the Urban areas and this could explain the relationship. As Pineapple is sold to local consumers it seems sensible that it is more likely to be grown in areas of higher population density, where there is a market. On the other hand, Forest and Miscellaneous areas tend to be in regions with low density, and low population density is an obvious characteristic of Forest areas (Trisurat et al., 2019).

To conclude, the regression analysis result shows that all the socio-economic factors have some effect on the distribution of Forest and Urban. Land right was found to be the most important factor. Land tenure is required not only for Urban, but also for crop areas, which require land where there is some kind of right. Land with no right was most likely to be Forest or Maize. This also makes sense, as the Forest areas tend not to be owned by anyone. For other land use categories, only some of the socio-economic factors were found to be important.

Lam Mun Sub-watershed (LMSW)

Biophysical factors: This refers to the impact of biophysical factors, which is similar to MCSW. Rice and other crops have a negative relationship with soil fertility. The exception is Eucalyptus. Rice is an important crop especially in the Northeastern part of Thailand. The results show that, in this study area, the areas with lower soil fertility are more likely to be Rice and other main crops. This area generally has low fertility soils and saline soils. The farmers' decision-making gives the priority to using their land as paddy fields before selecting to grow the other choices of crop, even though their land has low fertility. They grow Rice to feed their family and keep the seeds for the next crop, which is a tradition from their predecessors. Eucalyptus is on the high fertility land in this study area. Eucalyptus can grow in saline soil and has enough endurance to grow in flooding or drought areas. Most of the Eucalyptus area is near to the Forest and has a good soil with lots of organic matters, which is typical for Forest soils.

The steepness of the slope certainly affects the probability of Forest, Urban, Miscellaneous, Rice, Cassava and Eucalyptus while slope has no effect on Sugarcane, Rubber and Other Agricultural. This study area is mainly plain or lowland that faces the problem of flooding in the raining season, especially in the areas which are near to the rivers. Most of the existing Rice is located on a lowland plain (slope 0-2%) which naturally results in a negative relationship between probability of Rice and slope (Zhao et al., 2018; Siagian, 2019a). By contrast, steeper slopes have a higher probability of being Forest, Urban, Miscellaneous, Cassava or Eucalyptus. It is reasonable to expect that steep slope has a positive relationship with Forest as this is similar to MCSW (and to other areas in Thailand). However, the area of Urban in LMSW has a positive relationship with slope because the area that has no flooding is appropriate for villages and these areas need to be on gentle or steeper slopes to avoid flooding. Moreover, around 84% in the total area of this study area is in the slope category 0-1%. This naturally results in a positive relationship between probability of Forest and slope and a negative relationship between probability of Rice and slope, as Rice is occupying the lowland plain areas.

Soil drainage is included in many attempts to model land use change (e.g. Rogger et al., 2017 and Ozsahin et al., 2017). Areas with good drainage have a high probability of being other crops such as Sugarcane, Cassava, Rubber and Eucalyptus. Well drained areas are associated with sandy loam soil, silt loam soil and silt soil. On the other hand, the areas with poor drainage are more likely to be Rice or Other Agricultural. Poorly drained areas, which are associated with sand clay, silt clay, and clay soil are suitable for Rice.

Rainfall in this area figures in all of the models, but it is not a strong predictor. Most of the Rice in this area is grown in paddy fields in a rainfed agricultural area that has a water requirement in the growth period of about 400-800 mm or annual rainfall of around 800-2000 mm (Food and Agricultural Organization, 1976). This naturally results in a positive relationship between probability of Rice and rainfall.

In conclusion, all of the biophysical factors have some effect on the distribution of Rice, Cassava, and Eucalyptus. The water for Rice is important and soil drainage (poorly drained soil) and rainfall are significant factors for Rice. The relationship between the biophysical factors and the presence of Eucalyptus is the opposite of Rice. The distribution of Rice is negatively related with soil fertility, soil drainage, and slope, whereas the distribution of Eucalyptus is positively related with these factors.

Socio-economic factors: All accessibilities have a negative relationship with Urban and Rice The results show that these land use categories tend to be located nearer the river. The accessibilities are also driving factors for the presence of Forest and other crops, although this excludes Cassava and Eucalyptus, which do not have any relationship with distance to the agricultural market. When an area is close to the road and river, but is far from the market, this leads to a higher probability of the presence of Forest. For the Forest in this study area, there are not only the natural Forests but also the areas of reforestation by the villagers, and the village is located near to these conservation Forest areas. This results in areas near to the road being more likely to be Forest.

Land right has a strong positive relationship with Urban, Rice and Other Agricultural as all of these require land tenure. There is a negative relationship between land right and Forest or Eucalyptus. Land right is the strongest socio-economic predictor of Forest, which is typically found on land with no right. This is a characteristic feature of Forest area, which are not owned by anyone, but belong to the government.

In addition, Urban, Sugarcane, Cassava and Other Agricultural areas are more likely to occur in the areas of higher density population. These land use types have a positive relationship with population density in the model. High population is a typical characteristic of the Urban areas, which explains the relationship. However, Forest and Rice are more likely to be located in areas of low population density. Use of machinery for growing Rice is increasing in this area. Rice can be grown in low density areas as it no longer requires a large amount of manual labour to grow it.

To conclude, the regression results show that all the socio-economic factors have some effect on the distribution of Urban, Rice and Other Agricultural. When farmers own their land (legal right), it is easy to decide to change or keep the same crop in their land. Urban does indeed require the legal right to the land.

The regression analysis shows that the biophysical factors (such as soil fertility, slope, and annual rainfall) are important for influencing agricultural land uses in both study areas. It was also evident that different factors influence different crops. Interestingly, the relationship of the crops to the biophysical factors was not the same in both areas. This indicates local differences in the characteristics of the study areas and in agricultural practice.

4.3 CA-Markov models

The CA-Markov, Multi-Criteria Evaluation (MCE) and Land Change Modeller (LCM) modules are different functions which are all available within TerrSet in IDRISI. Figure 4.5 provides a comparative overview of the modelling approaches.

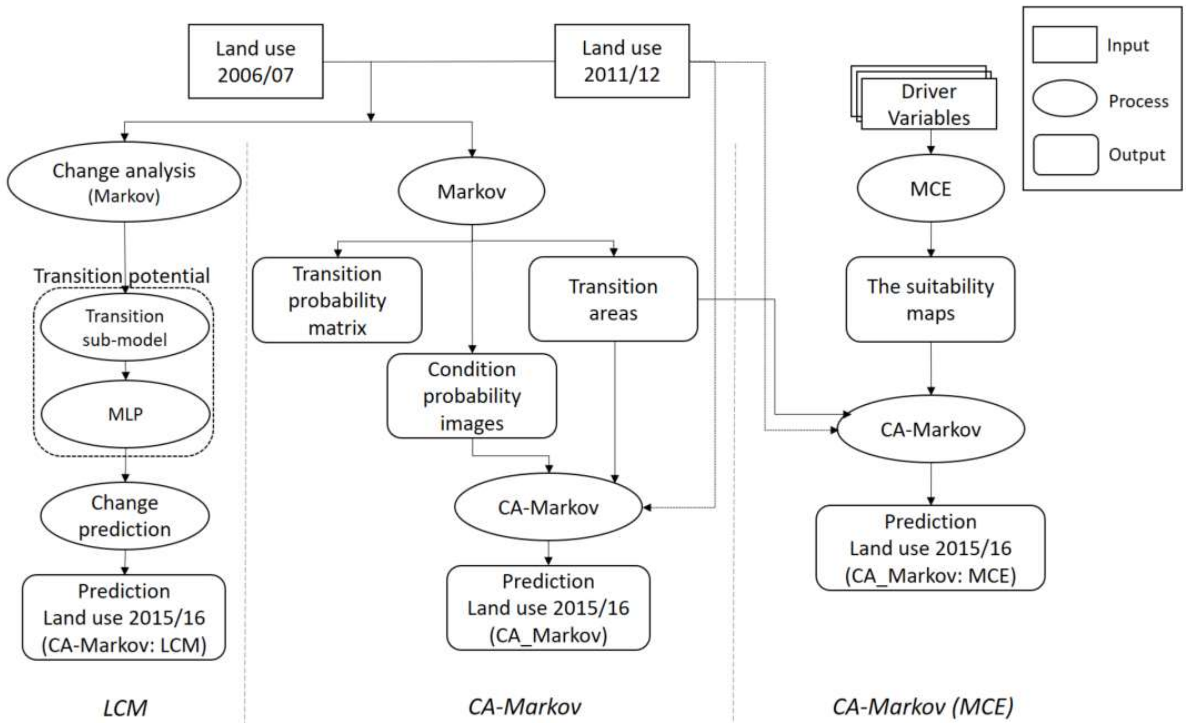


Figure 4.5 CA-Markov, MCE, and LCM modules in TerrSet to predict land use change

CA-Markov is an integration of a Markov chain procedure and a CA filter, in which the Markov chain model provides the random process system for the change prediction. CA-Markov combines and applies the advantages of Markov chain and CA for land use modelling. The model uses the Markov chain output result and applies a basic CA filter that can be made through the spatial geo-reference file to predict the land use change. Put simply, CA in TerrSet is typically used in dynamics where the future states of a cell depend on its current state and the state of neighbouring cells. The prediction analyses the later land use map as used with the Markov chain model, the transition areas (which are created by the Markov chain), and the transition suitability maps. The changing rule is conducted by a filter. The filter is the key to the CA cells interaction. This assigns the down-weight of the suitability of the cells.

The Markov chain model, or Markovian transition estimator analyses a pair of land use maps. The outputs of this process are a transition probability matrix, transition areas and a set of conditional probability images. In the transition probability matrix, the probability of transition between any pair of land uses is expressed as a fraction between 0 and 1. A value of 0 means there is no chance of transition. The estimation number is relative frequency of transitions observed over the entire time period that they can be used to predict from the results of estimation. The *transition areas matrix* records the number of cells that are predicted to change over the specific prediction time. The output of the transition probability matrix for MCSW showed that the land uses with the highest likelihood to change were Maize, Pineapple, Rubber, and Other Agricultural, while for LMSW the land uses which were most likely to change were Sugarcane, Cassava, and Other Agricultural.

The Markovian transition estimator inputs are a pair of land use maps, which in this study were land use map 2005/06 (earlier year) and 2011/12 (later year). These maps were used to simulate land use in 2015/16. The transition probability matrix shows the probability of each land use category changing to every other category (see Table 4.6 and Appendix Tables 3.1and 3.2). The transition areas matrix or Markov transition areas show the number of cells that are changed after the specific times (see Table 4.7 and Appendix Tables 3.3 and 3.4). The conditional probability images are calculated as predictions from the pair of land use maps that show the probability of each land use category being found at each cell over the specific period of time.

Table 4.6 An example of a transition probability matrix (MCSW)

Markov matrix for 2007-2012		2007								
		FOR	URB	MIS	RIC	MAI	PIN	COF	RUB	OTH
2012	FOR	**0.8666**	0.0006	0.0030	0.0002	0.1020	0.0005	0.0109	0.0098	0.0065
	URB	0.0009	**0.9918**	0.0000	0.0000	0.0010	0.0000	0.0063	0.0000	0.0000
	MIS	0.0022	0.0242	**0.7807**	0.0139	0.0568	0.0479	0.0000	0.0393	0.0349
	RIC	0.0000	0.0033	0.0003	**0.9609**	0.0130	0.0024	0.0000	0.0033	0.0167
	MAI	0.0023	0.0105	0.0397	0.0124	**0.6265**	0.0604	0.0633	0.0873	0.0977
	PIN	0.0000	0.0062	0.1691	0.0347	0.0019	**0.6986**	0.0000	0.0542	0.0354
	COF	0.0000	0.0266	0.0000	0.0133	0.0033	0.0000	**0.9052**	0.0070	0.0446
	RUB	0.0000	0.0000	0.0175	0.0158	0.0000	0.3234	0.0000	**0.4295**	0.2138
	OTH	0.0031	0.0064	0.0200	0.0089	0.3660	0.0078	0.1008	0.0444	**0.4428**

Table 4.7 An example of a transition area matrix (MCSW)

Markov matrix for 2007-2012		2007								
		FOR	URB	MIS	RIC	MAI	PIN	COF	RUB	OTH
2012	FOR	**8516**	6	29	2	1002	5	107	96	64
	URB	1	**970**	0	0	1	0	6	0	0
	MIS	2	20	**629**	11	46	39	0	32	28
	RIC	0	11	1	**3165**	43	8	0	11	55
	MAI	9	39	149	47	**2356**	227	238	328	367
	PIN	0	3	70	14	1	**289**	0	22	15
	COF	0	22	0	11	3	0	**733**	6	36
	RUB	0	0	11	9	0	194	0	**258**	128
	OTH	5	11	35	16	639	14	176	78	**774**

The difference between CA-Markov, MCE, and LCM relates to the way they simulate the change using transition probability or suitability maps. The different processes are schematized in Figure 4.5 above. CA-Markov uses Markov Chain matrices to determine the number of changes. MCE uses the suitability maps for each land use category based on weight of evidence (the variable factors) which is calculated using Multi-Criteria Evaluation. The change in land use in this model depends upon the weight allocated to the criteria (e.g. soil fertility, distance to road etc.). LCM generates the transition probability maps from one land use category to another category using Multi-layer perceptron (MLP) (see Section 4.3.3). The MLP imports the map of independent variable factors and analyses the transition potential for each category to create the transition probability map. While the underlying processes are similar, MCE and LCM incorporate additional 'variable factors' (Table 4.1, Section 4.1) to calculate the probability of transition or suitability maps from one land use to another. In contrast, CA-Markov only generalizes trends from historical land use.

4.3.1 CA-Markov

The CA-Markov module in IDRISI TerrSet integrates the function of the CA filter and the Markov process, using conversion tables and the conditional probability of the conversion map to predict the future state of the land use (Figure 4.5). The specific modelling process consists of the determination of the transition rules, determination of the CA filters, determination of the starting point and the CA iteration number.

The first process is the determination of the transition rules, through Markov chain analysis of land use trends (e.g., Tables 4.6 and 4.7). The basic land use map/image used the map between the baseline year (which in this study is the land use map year 2006 (for LMSW) and 2007 (for MCSW)), and the later year (2011 (for LMSW) and 2012 (for MCSW)). The suitability map in IDRISI refers to the suitability of a cell or a pixel for a specific land use.

The second process is the determination of the CA filters, which can assign the down-weight of the suitability of the cells. These can be changed according to the existing adjacent cellular state. The standard 5×5 contiguity filter was used as the neighbourhood definition in this study.

The third process is the determination of the starting point (in time) and the CA iteration number which took the year 2006 (LMSW) or 2007 (MCSW) as a starting point. The number of CA-iterations was set at 9 in order to simulate the spatial pattern of land use change maps for 2015 (LMSW) and 2016 (MCSW).

4.3.2 Multi-Criteria Evaluation (MCE)

Multi-Criteria Evaluation (MCE) in IDRISI TerrSet is an integrated CA-Markov/ Multi-Criteria Evaluation (MCE) procedure. The MCE module uses the CA-Markov change prediction analysis and the suitability maps.

The procedure of MCE to achieve the simulation result is to run the Markov module using the earlier land use map (2007 for MCSW and 2006 for LMSW) and the later land use map (2012 for MCSW and 2011 for LMSW). The Markov module generates transition probabilities and transition area (the same as the method for CA-Markov in Section 4.3.1).

The MCE module uses suitability maps for each land use category based on a supervised Multi-Criteria Evaluation. These suitability images or maps are normally derived from the MCE module and also build upon expert's or analyst's knowledge of the influences of the variable factors on land use categories. The suitability maps were prepared taking into account the driving factors for land use change and distribution (which are the factors shown in Table 4.2 of Section 4.1).

Looking at the determination of the weight for each factor in Table 4.8, the suitability maps for Rice for example might include criteria such as soil fertility, soil drainage, slope, annual rainfall, distance to road, distance to river, distance to the agricultural market, land right and population density. A score is calculated for each of the factors. The score for the individual factors is standardised using a standard scale to make comparison between different factors possible. Weights were determined based on interviews conducted with the land use experts (described in Section 3.1.2). As the experts did not make a distinction between the study areas in terms of criteria influencing the suitability of land for agricultural use, the weighting of factors was the same in the two areas. The given value of MCE weights is usually normalised to sum to 1 (a value of 0 means the factor is not important for land transition). Table 4.8 shows the weights used for agricultural land use categories evaluated in this study.

Table 4.8 The factor weights applied to agricultural land use categories in MCSW and LMSW

Variable factors	Factor weights
Soil fertility	0.0224
Soil drainage	0.0224
Slope	0.2663
Annual rainfall	0.1273
Distance to road	0.1273
Distance to river	0.0230
Distance to agricultural market	0.1273
Land right	0.0664
Population density	0.0788

Different variable factors have been given different levels of importance in the cells in the suitability maps. The results of evaluating the relative importance of factors indicated that slope was the most important factor followed by annual rainfall, distance to road, and distance to agricultural market. The slope plays the key role because it affects the distribution of land use categories (such as Forest or Rice), also it affects the rate of runoff and can cause accelerated soil erosion.

In addition, CA-Markov/MCE applies a filter to the change rule. The filter is intended to down-weigh the suitability of cells that are indirectly connected or distant from existing examples of that land use. For land use conversion, the cell should be suitable and near to existing neighbouring areas of that land use category.

4.3.3 Land Change Modeller (LCM)

The Land Change Modeller (LCM) from IDRISI is an empirical model that is used to predict the land use change dynamic; this involves preparing data, model building and model validation to enable land use change analysis and prediction. The change prediction process in LCM is an empirically driven process which proceeds in a stepwise mode moving from the first step, change analysis. LCM analyses the change between two land use maps of different dates. The second step is the transition potentials modelling, which identifies the potential of land to transition based on the underlying driving variables and the last step is the change prediction, which represents the consequences in terms of the future land use (Eastman, 2016).

LCM is used to analyse and predict the land use change between two periods. The basic principle of the model is to evaluate the change trend or historic tend from the earlier year to the later year, assessing the change from one land use to another land use and empirically modelling relationships with the influencing driving factors (Eastman, 2016). For instance, soil fertility, soil drainage, slope, annual rainfall, distance to road, distance to river, distance to agricultural market, tenure, and population density. This is used to predict the land use pattern based on the historic trend using CA-Markov. LCM progresses in a stepwise mode, from change analysis to transition potential modelling and change prediction. The diagram of LCM analysis is shown in Figure 4.5.

4.3.3.1 Change analysis

The first step of LCM is change analysis which was done by using two land use maps from different years. The identified changes present a transition from one land use to another land use, which can be shown in graphic forms such as a change analysis map. The basic principle of this module is to establish the trend of land use change. The changes of this model were evaluated by gains and losses in different categories (Eastman, 2016).

In terms of the change analysis process, this used the earlier land use map (2007 for MCSW and 2006 for LMSW) and the later land use map (2012 for MCSW and 2011 for LMSW), for the analysis and detection of changes. The outputs of the change analysis were the number of gains and losses in each land use category, change map and the transition map.

4.3.3.2 Transition potential modelling

The second step of LCM is transition potential modelling. Transition potential modelling uses a set of sub-models to indicate which explanatory variables or driving forces are important. A transition sub-model can establish a single land use transition or a group of transitions, which are based on the same underlying factors for the historical changes. The transition sub-model uses Multi-Layer Perceptron or MLP (Eastman, 2016). The results of the MLP analysis are a number of transition potential maps (one for each land use category) which build on the change analysis process (described in Section 4.3.3.1).

Generally, TerrSet recommends Multi-layer perceptron (MLP). MLP is the default in LCM and can be used to model multiple transitions at the same time. The MLP neural network technique starts training on the samples that are provided in the form of cells or grids and relies on neural networks. The MLP neural network is a sort of feedforward artificial neural network, which is the flow direction from input layer through hidden layers to output layers. It then identifies the relationships, which are non-liner or multi-layer mode. The algorithms calculate by weighing input value nodes, hidden layer nodes and output layer nodes procedure. The results of MLP are used to predict land use change, and the potential for land use transition or persistence. (Eastman, 2016; Gibson et al., 2018).

In terms of the practical application of MLP, this technique was applied by creating nine sub-models. For MCSW these were allocation: to Forest, to Urban, to Miscellaneous, to Rice, to Maize, to Pineapple, to Coffee and Tea, to Rubber, and to Other Agricultural. For LMSW, these were allocation: to Forest, to Urban, to Miscellaneous, to Rice, to Sugarcane, to Cassava, to Rubber, to Eucalyptus, and to Other Agricultural. At this stage, the LCM was operated in the automatic mode.

4.3.3.3 Change prediction

The third step of LCM is change prediction using the change trend and the transition potential model. The change number of each transition can be modelled through the Markov chain analysis and also on a transition matrix. The analysis result shows two prediction types which are 'hard' and 'soft' predictions. Hard prediction is the projected map where each cell is allocated one land use type. Soft prediction is where the probability of a cell changing is expressed as a value between 0 and 1. The hard prediction map used for model validation, is the next step after model set-up and calibration (Eastman, 2016).

Regarding the change prediction step, the prediction in this study was a scenario for 2016 (MCSW) and 2015 (LMSW). This step is responsible for determining the number of changes to each land use category in 2015 and 2016 using Markov Chain analysis. The hard prediction outputs are a prediction map for 2016 (MCSW) and 2015 (LMSW).

4.4 Agent-based model (ABM)

The ABM software used in this study was NetLogo (Wilensky, 1999), which has GIS capability and is open-source software. NetLogo has been used in different disciplines across the social sciences, where there is a need to understand the integration of biophysical and socio-economic factors with human decision-making.

Model description

The ABM model used in this study aims to simulate the future land use under the influence of driver variables, whilst also taking into account the farmers' decisions on the choice of land use, which were used to allocate the land use in each cell. The aim was to generate a historical sequence of land use change from 2007 to 2016 in MCSW, and from 2006 to 2015 in LMSW.

This model consists of entities which are the landscape, comprising of individual cells (containing land categories and other attributes), individual farmers (which are grouped into *open to change* and *no wish to change* categories), and the environmental variables (soil fertility, soil drainage, slope, annual rainfall, distance to road, distance to river, distance to the agricultural market, land right, and population density).

The landscape of land use cells consisted of patches or grid cells which covered the full extent of each study area. The model world needs to specify how large the environment is (to set the maximum x and y coordinates for patches). Regarding the model world of the study areas; Mae Chan Sub-watershed (MCSW) and Lam Mun Sub-watershed (LMSW) consisted of 276×163 patches and 401×189 patches, respectively. Each grid cell represented a 250×250 m area. The model ran for nine years (2006/07 to 2015/16) for validation (one time step in the model for each year). The farmers' crops were identified as the main agricultural land use categories in the study areas (MCSW; Rice, Maize, Pineapple, Coffee and Tea, Rubber and Other Agricultural and LMSW; Rice, Sugarcane, Cassava, Rubber, Eucalyptus, and Other Agricultural).

Input map and parameter values

The input spatial maps and parameter values for the ABM were based on sources described previously such the land use maps discussed in Section 4.1.

The farmers attribute data were collected from farmer interviews in the study areas to assess how farmers' behaviour relates to decision-making about which crops to cultivate (described in Section 3.1.2 of Chapter 3). Farmer groups were derived from interviews with 50 farmers in each of the study areas. The survey data was integrated with spatial data on land use and the variable factors.

Farmers are agents in the model world and interact with the agricultural land use grid cells or patches. Two groups of farmers (those *open to change* or with *no wish to change*) were identified from various farmer characteristics and behaviours (tenure, farm size, age, and education). The farmer decisions depend on a number of rules that were derived from qualitative analysis of the interview results. A simple approach to presenting the decision making in Agent-Based Models (ABM) is to use decision trees (Rounsevell et al., 2012). The decision tree applied in this analysis is shown in Figure 4.6.

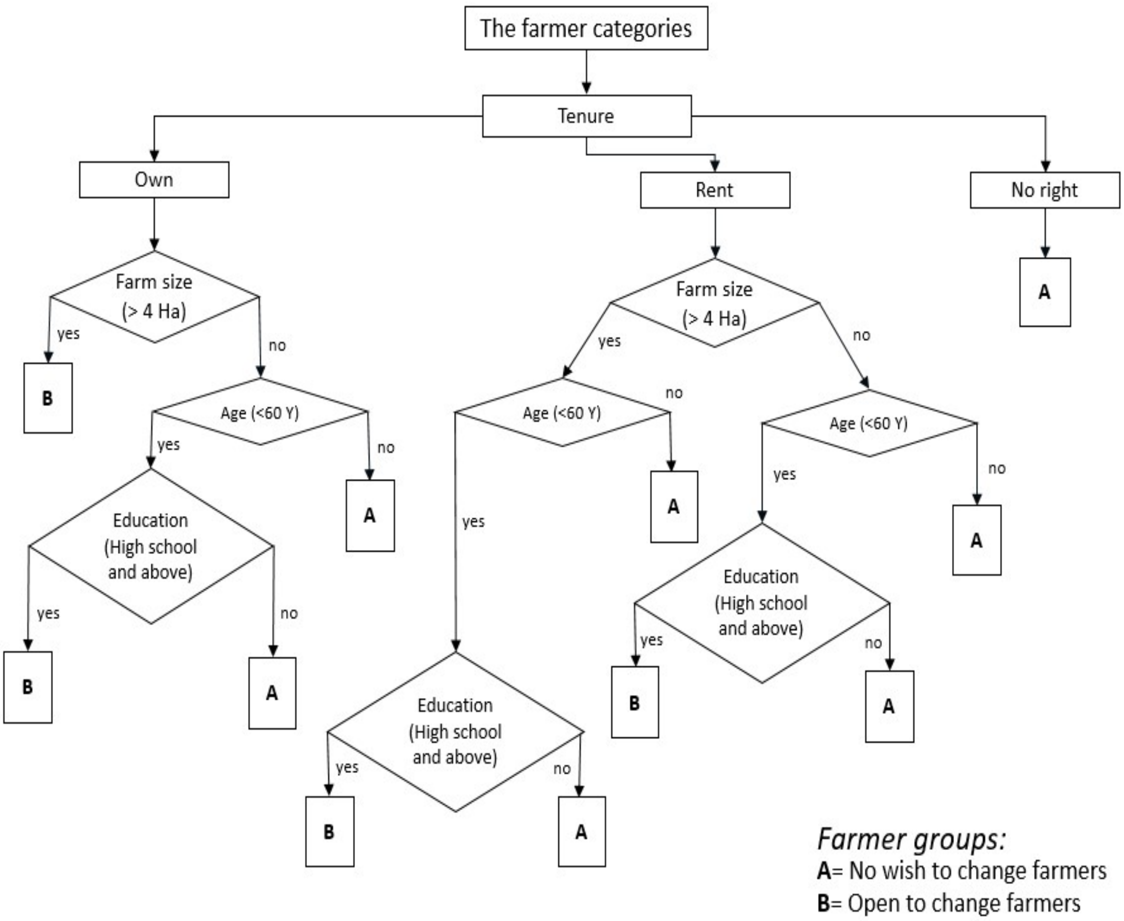


Figure 4.6 The decision tree of the farmer groups classification

The character of *no wish to change farmers* tended to be those with no right or no tenure, a small farm size (less than 4 hectares), older than 60 years and with education lower than high school. On the other hand, the *open to change farmers* tended to be those with their own land or renting the land, larger farm size (greater than 4 hectares), younger than 60 years old, and with better education (high school level or above). The percentage in each group was calculated following classification using the decision tree.

For MCSW 58% were *open to change* farmers, and 42% were *no wish to change* farmers. With LMSW the percentages were 54% and 46% respectively. In the ABM the farmers were only assigned to Agricultural land use patches (i.e. excluding Forest, Urban and Miscellaneous) and were randomly assigned to these based on the above proportions for each sub-watershed.

The model runs annually, with farmers becoming older through time until they reach the age of 80 after which they are assumed to die, and a new farmer family replaces them. The new family can display either the same or a different behaviour, according to the category assigned.

Process overview and scheduling

The model requires three main categories of input data to assess the effects of biophysical and socio-economic factors on land use decisions; 1) trends in land use change, 2) land use and agricultural transition suitability, and 3) a filter reflecting the farmers' attitude toward change (i.e. *open to change* or *no wish to change*).

Three types of entity influence the behaviour of each grid cell during a time interval. These are; 1) the environmental conditions in the grid cells or spatial units (land use categories and variable factors), 2) the dynamic agents (i.e. individual farmer households), and 3) the interaction between the agents via a neighbourhood effect rule.

The neighbourhood rule (within the agricultural land use categories) was based on the four adjacent cells in cardinal directions surrounding a central target cell (i.e. the Von Neumann neighbourhood, Crooks et al, 2019). This rule did not alter the probability of land use change occurring but did influence what type of change took place. When three or four cells of neighbouring cardinal cells had one land use, then the central cell was altered to that land use. For example, if the three or four cardinal cells were Maize and the target cell is another crop then this cell would change to Maize. Where the surrounding cells were all different, one of the cells was chosen at random. Where two cells were the same and others different one of the land uses was chosen at random. The rule determining the interaction of agents allowed change to occur during the next time step (year = year +1) i.e. in the following year.

Figure 4.7 illustrates the overall ABM process. The model inputs are the transition probability and suitability of change from MCE (Section 4.3.2).

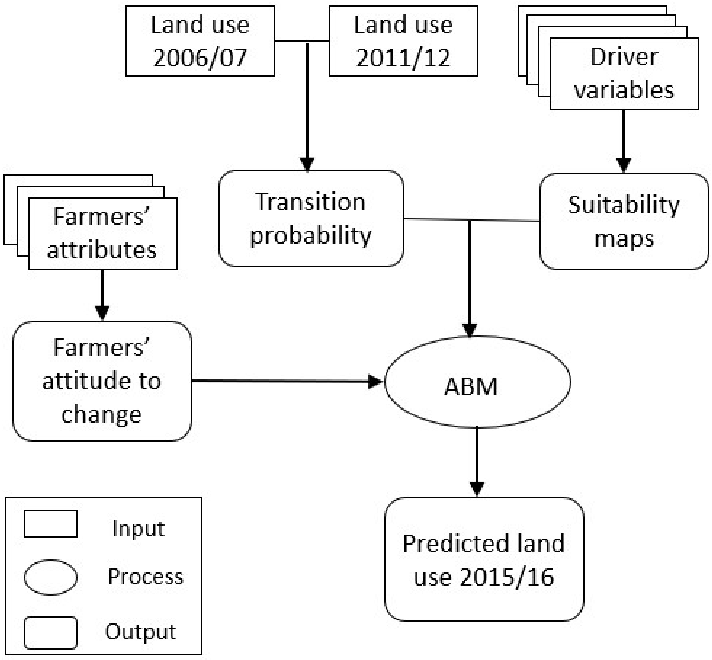


Figure 4.7 The ABM method used to predict land use change

A number of previous implementations of the ABM approach to land use modelling have incorporated transition probabilities and suitability maps (e.g. Truong (2017) and Shaaban et al. (2018)). These provided representations of change dynamics and the influence of environmental conditions. A similar approach was taken in this ABM with the inputs drawn from the MCE model to improve the overall efficiency of the modelling process (by sharing inputs) and facilitating comparison to allow the benefits of the additional features in the ABM to be evaluated.

Model simulation

Figure 4.8 presents the processing steps which begin with the data on the two groups of farmers. This acts as a filter in the model which is applied at each time step (i.e. year) until the final year. Farmers (agents) are assigned to the agricultural land patches. As shown in the diagram, land with *no wish to change farmers* will not change use. Where farmers are open to change, the land allocation is determined by two modules which are the transition suitability and the neighbourhood rule. Thus, the neighbourhood rule only influences where the change occurs, not whether it takes place.

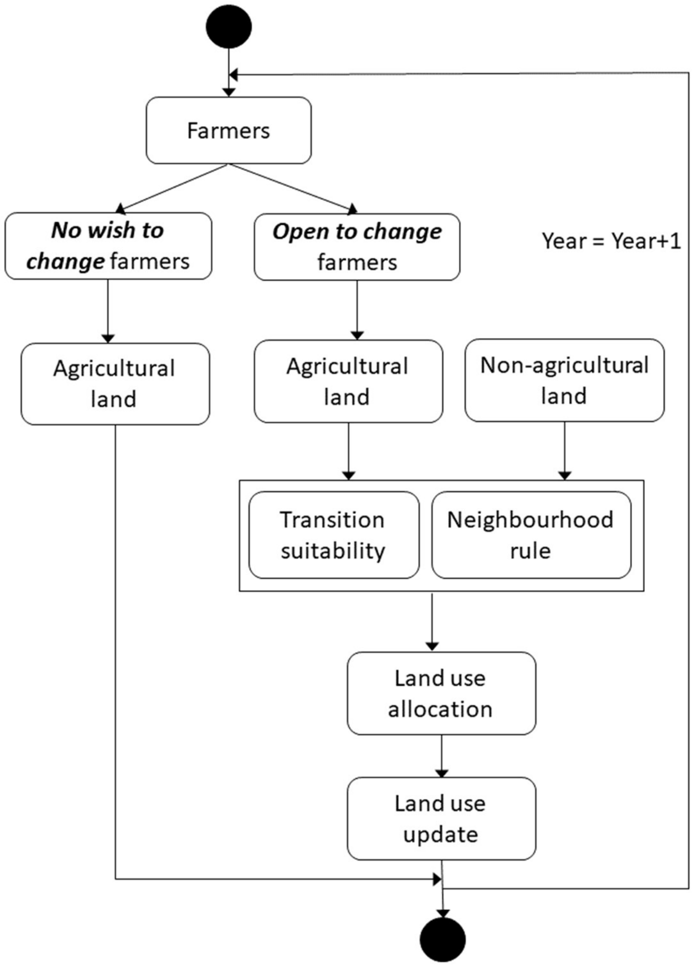


Figure 4.8 The model simulation run process

The land use allocation is updated (changed) each year (one year time steps). The quantity of each of the nine land use categories was exported at the end of the process to analyse the change in land use.

4.5 Summary

This chapter has described the parameter set-up and calibration process. This study predicted land use change using five modules; Dyna-CLUE, three modules within IDRISI TerrSet (CA-Markov, Multi-Criteria Evaluation (MCE), Land Change Modeller (LCM)) and an Agent-based model (ABM).

The driving factors (biophysical and socio-economic) were of three different types: ordinal (soil fertility, and soil drainage), continuous (slope, annual rainfall, distance to road, distance to river, distance to the market and population density), and dichotomous (land right). Some of the factors vary between the study areas, for example, slope and annual rainfall, while some of the factors have a similar range such as soil fertility and soil drainage.

The model set up provided insights into the relationship between the variable factors and the distribution of the different land uses. For instance, it revealed that the socio-economic factors had some effect on the distribution of Urban, Rice and Other Agricultural. It was also found that biophysical factors (such as soil fertility, slope and annual rainfall) were important for influencing agricultural land uses in both study areas. Interestingly the relationship of the crops to biophysical factors was not the same in both study areas.

The spatial distribution of driving factors and land use were in a common raster format for all models, but there were differences in the model set-up. Dyna-CLUE has multiple processes which require calculations to generate parameters for the model to run. ABM has a complicated process where the steps of calculation need to be designed, and time is also required for coding the model rules. CA-Markov, MCE and LCM are based on a similar process which starts with the Markov matrix preparation. Due to the way model processing is constructed, it is relatively quick to alter parameters and run the model again.

The next chapter presents the validation results for the models described in this chapter.

Chapter 5 | Validation

The previous chapter (Chapter 4) described the calibration process for Dyna-CLUE, the three IDRISI TerrSet modules (CA-Markov, Land Change Modeller, Multi-Criteria Evaluation) and the Agent-based model (ABM). This chapter focuses on the validation assessment of these models within Mae Chan Sub-watershed (MCSW) (Section 5.1) and Lam Mun Sub-watershed (LMSW) (Section 5.2).

The validation process combines the strengths of two different approaches, a visual comparison of correct/incorrect simulation maps and an overall statistical comparison using error matrices (measuring the overall accuracy, and comparing user's accuracy, and producer's accuracy) (see Section 3.1.2 for a definition).

The visual analysis allows assessment of spatial patterns which cannot be ascertained through global statistical measures of accuracy. The latter provides an objective quantification of the mismatches between modelled data and a reference surface.

Both measures, however, assume that there are no errors in the reference map. Other uncertainties may be introduced due to modelling with other imperfect data. High quality datasets were therefore chosen to minimize these errors.

Given these uncertainties, and an acknowledgement that the models only output the most probable land use based on likely scenarios, the purpose of the validation was to evaluate model performance against a baseline. More specifically, the accuracy assessment sought to evaluate whether specific crops can be modelled and, if so, whether some crops are easier to model than others? The combination of the visual assessment and statistical assessment can help to answer these questions.

5.1 Mae Chan Sub-watershed (MCSW)

5.1.1 Comparison of correct/incorrect simulation maps for Mae Chan Sub-watershed

The comparison of the correct/incorrect simulation maps' compares the reference map (2016, Figure 5.1) with model outputs from Dyna-CLUE, CA-Markov, MCE, LCM and ABM to create binary maps where each cell is either correctly or incorrectly simulated.

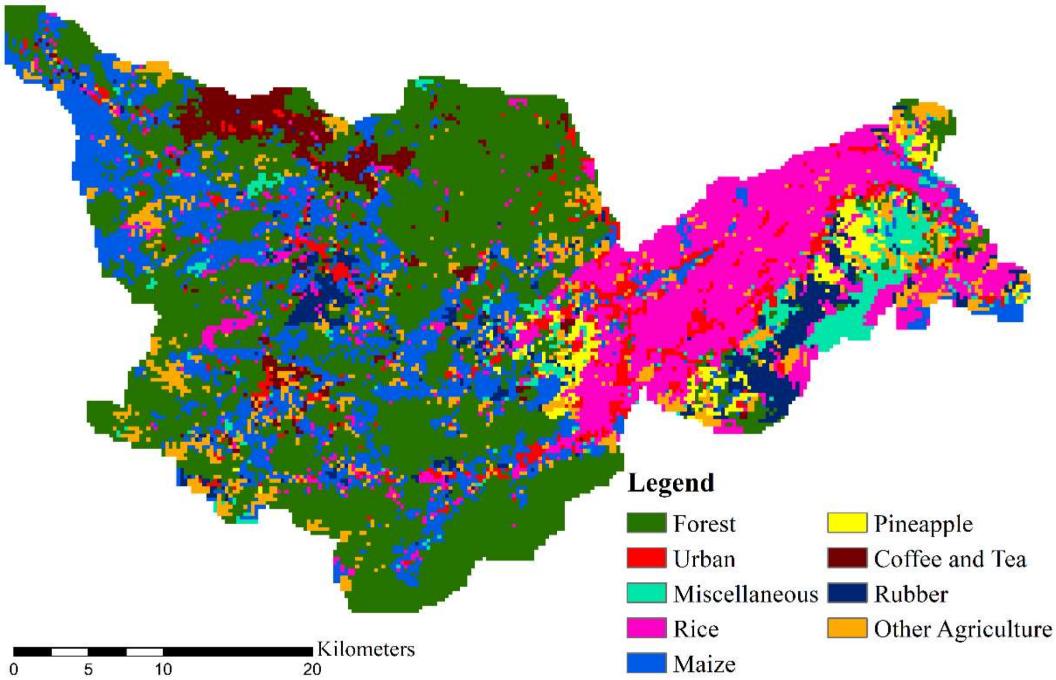


Figure 5.1 Land use map 2016 for MCSW (i.e. the reference map)

Figures 5.2 show the correct/incorrect simulation maps from Dyna-CLUE, CA-Markov, MCE, LCM and ABM, in MCSW.

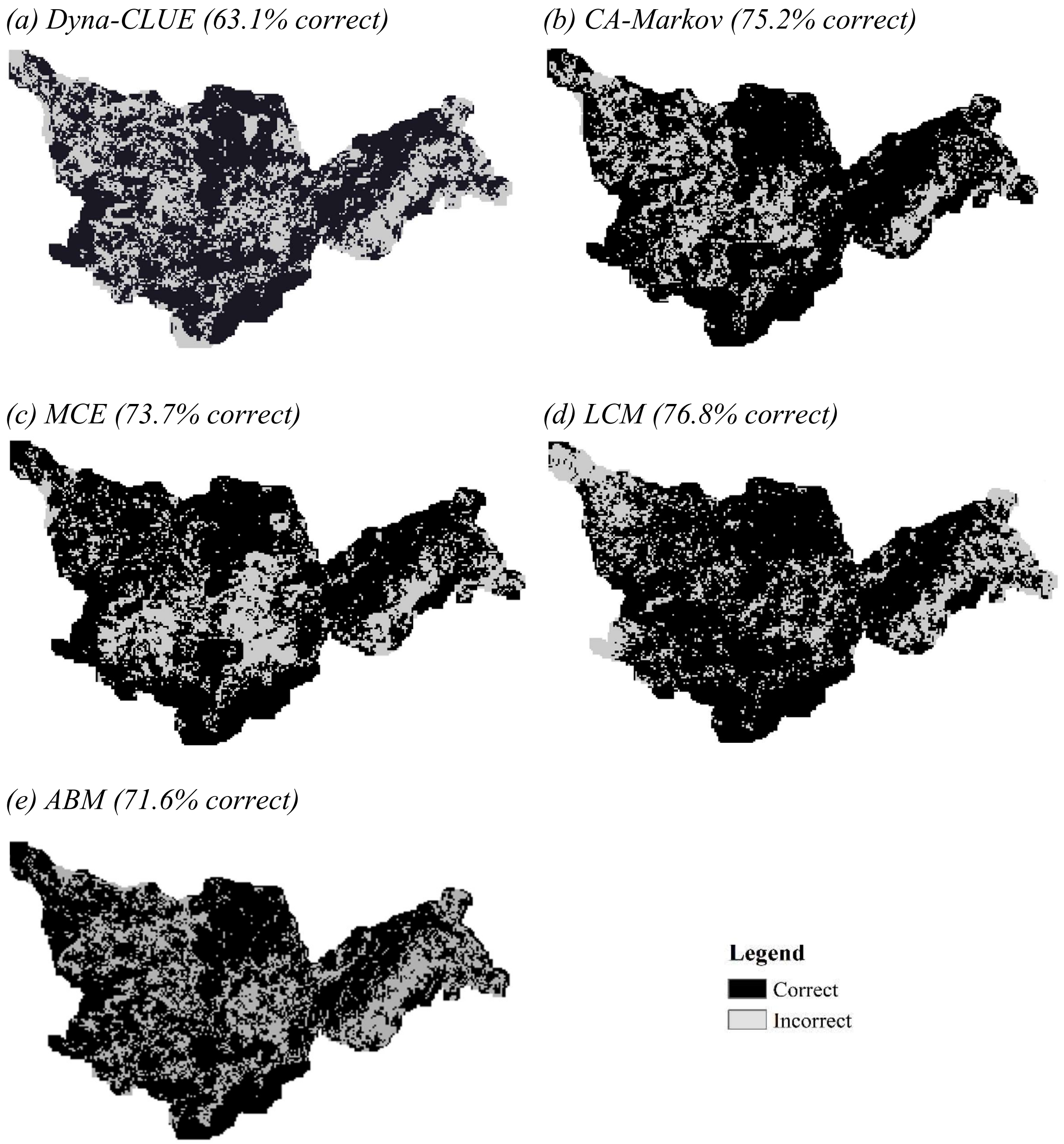


Figure 5.2 Correct and incorrect simulation maps for MCSW from (a) Dyna-CLUE, (b) CA-Markov, (c) MCE, (d) LCM, and (e) ABM. Correct simulation shown in Black, incorrect simulation shown in Grey.

From Figure 5.2, four models correctly simulate over 70% of the study area and the spatial distribution of 'correct' cells is broadly the same for these. The LCM binary map (Figure 5.2(d)) shows the largest area with correctly simulated land use (76.8%), while the Dyna-CLUE binary map (Figure 5.2(a)) shows the smallest area with correctly simulated land use (63.1%).

Considering the distribution of correct and incorrect cells, some similarities can be observed across the models. For example, the large contiguous area of Rice (Figure 5.1) is simulated quite well by all the models but the more diverse areas, in which several land use categories are located, were simulated differently across models.

The binary map of Dyna-CLUE (Figure 5.2(a)) shows that the majority of the correctly simulated land use occurred at the edges of the area, in the north-central and south-central regions. Dyna-CLUE simulated well the contiguous areas of Rice and Forest, but many of the other areas are not simulated well. These regions often correspond to the forested areas within the study area. Both LCM and Dyna-CLUE perform poorly in the north-western corner of the study area (which borders Myanmar).

The binary map of CA-Markov (Figure 5.2(b)) also simulated the contiguous area well (similar to Dyna-CLUE), but it simulated the Maize areas poorly. The LCM (Figure 5.2(d)) showed the largest area with correct simulations, but this model still did not simulate the area of mixed land use categories well (e.g. in the east). The MCE (Figure 5.2(c)) was also poor in the mixed-use areas, (in the central portion of MCSW).

The ABM map (Figure 5.2(e)) showed similar areas of correct simulation to MCE, but in the central portion of MCSW, the ABM shows more correctly simulated cells than MCE.

Comparing all binary maps in Figure 5.2, land use categories in the south-east and central areas were poorly predicted across all models. Land use in these areas is relatively easy for farmers to change i.e., to change from Rice to Pineapple or Rubber. This type of change can be observed empirically in the area. In the south-east, the suitability mapping (for different agricultural land use categories) could not distinguish between the different crops (which have similar requirements). These factors likely combined, resulting in a low accuracy for Pineapple and Rubber in particular.

It is clear that there is agreement across some of the models for large parts of the study area. Figure 5.3 shows the spatial distribution of model agreement. Table 5.1 then shows the percent of times the cell was correctly simulated in each land use category, with how many models correctly simulated, which was calculated from Figure 5.3.

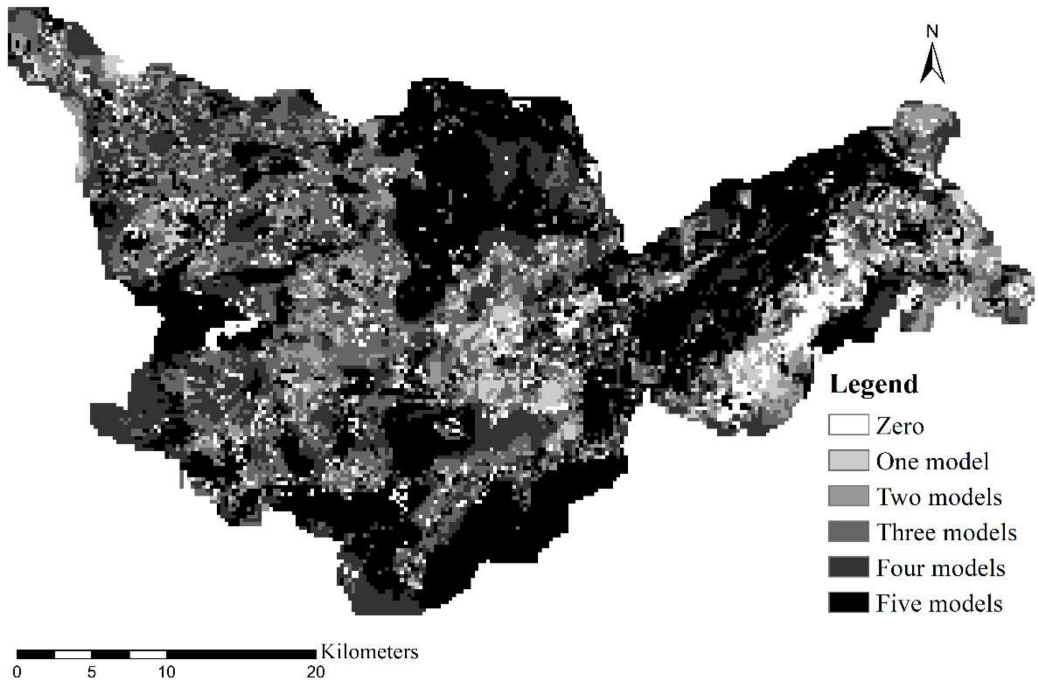


Figure 5.3 The number of times out of five that an individual cell was correctly simulated in MCSW. Correctly simulated shown from zero to five models in light to dark.

Table 5.1 The number of times out of five that a cell was correctly simulated in any given land use category.

Land use categories	Land use 2016 (cells)	Percent of cells correctly simulated					
		Zero	One	Two	Three	Four	Five
Forest	9,175	0.0	0.9	4.1	15.8	26.3	52.9
Maize	3,984	3.1	11.3	16.2	33.7	26.4	9.2
Rice	3,528	8.0	3.6	6.4	9.5	21.3	51.2
Other Agricultural	1,631	16.7	16.4	32.7	21.3	11.1	1.9
Urban	980	0.0	1.1	0.6	7.8	14.0	76.5
Rubber	861	35.8	17.3	20.7	20.0	6.3	0.0
Coffee and Tea	808	2.7	0.2	4.0	47.8	35.6	9.7
Miscellaneous	779	5.9	6.3	12.2	28.1	17.2	30.3
Pineapple	484	14.5	10.7	19.2	40.5	12.6	2.5

There are large areas of agreement, where the model performed well from all five models, the correctly simulated areas (darkest in Figure 5.3) occurring in the north-central, the south-central and the north-east regions, which comprise the majority of the Forest and Rice areas (Table 5.1). These are areas where the land uses have essentially remained the same, making it easier to simulate.

The main areas of common agreement across by all models were the large expanses of Forest. This is because this is a contiguous area of a single land use category which has a small probability of being allocated to other categories (as it is a restriction area). Urban and Rice also showed a high accuracy with many cells being correctly simulated by all five models. Urban is highly unlikely to change to another use. Rice is easier to simulate because it forms a large contiguous area, because it is unlikely to change, and because there are strong environmental drivers.

The majority of the agreement between three or four models occurred around the central and the west region (Figure 5.3). The majority of the correctly simulated cells were Forest and Maize. Maize is often found in Forest areas and this suggests that in some cases models are able to correctly assign the land uses, but in other cases they are not. Areas with correct simulation from only one or two models mainly occurred in the central and the east region. A high proportion of Maize, Other Agricultural and Rubber fell into this category (Table 5.1).

The main areas where no models were correct (lightest shading) occurred in the eastern region (Figure 5.3), which is a zone of Rubber plantation. This is also reflected in the results by land use category (Table 5.1).

Looking at Rubber, there were a large number of cells (35.8%) which were not correctly simulated by any models. No cells were correctly simulated by all five models, and only 6.3% of cells, by four models. This indicates that Rubber was hard to simulate with any model. Coffee and Tea cells were often simulated accurately by three (CA-Markov, MCE, and LCM) or four models (Dyna-CLUE, CA-Markov, MCE, and LCM), and it was the same with Maize. Other Agricultural cells were often simulated correctly by just two models (CA-Markov and LCM), while 16.7% of Other Agricultural cells were not simulated correctly by any model. Some crops therefore were easier to simulate, while others proved difficult to simulate with any model.

The next section focuses on selected sample areas to see - and compare - the performance from each model.

Five sample areas have been selected to analyse the performance of the model simulation in MCSW in more detail. Figure 5.4 The blocks were chosen to focus on specific areas with heterogeneity in terms of type and distribution and to compare the performance of the models in those areas. Some blocks are simulated well, while others are not.

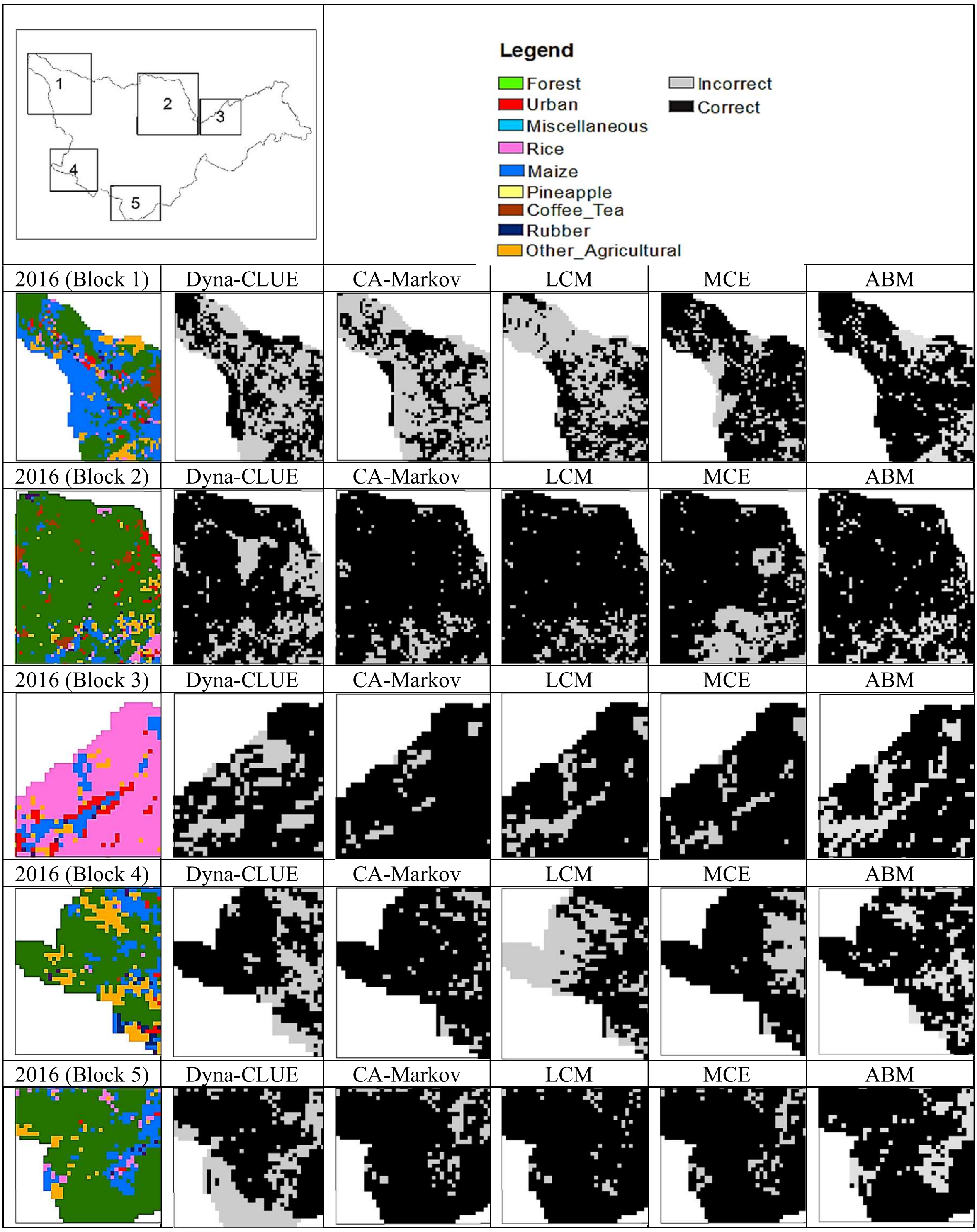


Figure 5.4 Correct and incorrect simulation blocks comparison in MCSW

The sample area Blocks 2, 3 and 5 show the majority correctly simulated cells, while blocks 1 and 4 show the fewest correctly simulated cells. This shows the variation in the model performance across the study area, which reflects the heterogeneity of the environment, and the ability to model some categories better than others.

CA-Markov models potentially work quite well where there are large patches of a single land use. A likely reason for this concerns the CA transition rule, which depends on the neighbourhood filter or CA-filter (see more in Section 4.2.2), where the factors are of a continuous (as opposed to categorical) type.

Dyna-CLUE, LCM and MCE would appear to work less well where there are large patches of multiple land uses, such as in Blocks 1 and 4. The reality map of Blocks 1 and 4 show many categories of land use such as Urban, Maize, Coffee, Rubber and Other Agriculture. The heterogeneity may possibly be the reason that Blocks 1 and 4 are difficult to simulate well.

The next section analyses the detail of the accuracy assessment, using overall accuracy, user's accuracy, and producers' accuracy for MCSW.

5.1.2 Accuracy assessment for Mae Chan Sub-watershed (MCSW)

To perform a simulation, it is necessary to look more detail at the fitness of the result, hence an accuracy assessment to evaluate the map error is required. Summary details of the overall accuracy, producer's accuracy, and user's accuracy for the five models are given in Table 5.2. The result in Table 5.2 shows the overall model accuracy is greater than 63% for each of the five models.

Table 5.2 Comparison of validation from LCM, CA-Markov, MCE, ABM and Dyna-CLUE in MCSW, ranking the models from highest to lowest overall accuracy (in percent)

Land use	***LCM***				***CA-Markov***				***MCE***				***ABM***				***Dyna-CLUE***			
	Producer's Accuracy	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**	**Producer's Accuracy**	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**	**Producer's Accuracy**	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**	**Producer's Accuracy**	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**	**Producer's Accuracy**	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**
URB	98	89	94	**1**	91	88	90	**1**	87	84	86	**1**	100	70	85	**1**	88	96	92	**1**
FOR	88	95	92	**2**	76	96	86	3	75	94	85	**2**	90	76	83	**2**	87	79	83	**2**
RIC	88	95	92	**2**	79	97	88	**2**	76	94	85	**2**	73	82	78	**3**	71	84	78	3
COF	87	56	72	3	93	52	73	5	93	52	73	3	41	46	44	5	27	15	21	**8**
MIS	72	61	67	4	85	71	78	4	77	65	71	4	41	58	50	4	60	76	68	4
MAI	62	60	61	5	70	56	63	7	73	58	66	5	41	46	44	5	43	35	39	5
OTH	41	45	43	**7**	68	63	66	6	59	54	57	6	22	35	29	6	9	43	26	7
PIN	55	35	45	6	77	42	60	**8**	68	37	53	**7**	19	25	22	**7**	14	40	27	6
RUB	30	31	31	**8**	42	35	39	**9**	48	39	44	**8**	17	29	23	**8**	6	7	7	**9**
Overall Accuracy (%)	**77**				**75**				**74**				**66**				**63**			

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, PIN= Pineapple, COF=Coffee and Tea, RUB=Rubber, OTH=Other Agricultural)

LCM showed an overall accuracy of 77%, which was the highest. The user's accuracy ranged from 31% to 95%, while the producer's accuracy ranged from 30% to 98%. The broad range of accuracy indicates a severe confusion of Pineapple and Rubber with other land use categories (leading to low accuracy in these categories). Thus, Rice and Forest were found to be more reliable with a user's accuracy of 95%.

On the other hand, Dyna-CLUE, shows an overall accuracy of 63%, which was the lowest. The user's accuracy ranged from 7% to 96%, while the producer's accuracy ranged from 6% to 88%. The broad range of accuracy indicates a severe confusion of Rubber, and Coffee and Tea with other land use categories (leading to low accuracy in these categories). Urban was found to be more reliable with a user's accuracy of 96%.

The producer's accuracy for individual land use categories shows that for LCM and CA-Markov the accuracy is greater than 70% for categories such as Forest, Urban, Miscellaneous, Rice, Maize and Coffee and Tea. This high producer's accuracy value could lead to the conclusion that the simulation map is sufficiently accurate for use, however, looking at the actual condition of the land use, it is apparent that only around half of the cells simulated as Coffee and Tea were actually Coffee and Tea. In other words, for LCM, for example 87% of Coffee and Tea has been correctly simulated as such, but only 56% of those area simulated as Coffee and Tea were actually Coffee and Tea. The other 44% of those areas as simulated as Coffee and Tea were in reality in other land use categories such as Pineapple or Rubber (i.e. Coffee and Tea were dramatically over simulate). The correct allocation of the simulation or the confusion between land use category for each model can be seen in more detail in Appendix Tables 4.1-4.5.

The mean of the producer's and user's accuracies was calculated, and the land use categories were ranked in order of accuracy. Taking the average of the producer's and user's accuracy for LCM, CA-Markov, MCE, ABM, and Dyna-CLUE in MCSW, the highest ranked categories are Urban, Forest and Rice which are over 78% accurate across all models.

Forest and Urban are well simulated in all models. The elasticity of conversion of Forest and Urban means that they are more difficult to change than other land use categories and that is probably the reason for them to show a good simulation. Rice, on the other hand, has low elasticity of conversion, but in practice, it is simulated quite well because Rice is a staple food that the farmers will reserve (most of) their land for growing. Although the farmers have changed land use from Rice to field crops (e.g. Maize, Pineapple), it is not difficult to change back to Rice when the farmers are dissatisfied with the yield and benefit of the other crops.

On the other hand, Rubber comes out poorly in all the models with an average accuracy of less than 45% in each case. Rubber is a new plant in the area that has only been grown since 2006 (Section 3.2.3). The baseline data of MCSW was 2007. In 2007, there were very few Rubber cells. However, after 2007 the area of rubber expanded considerably. As a result, this is difficult to model accurately (because there is not much data to base the simulation on).

The results show that the producer's accuracy and users' accuracy for LCM, CA-Markov, and MCE are fairly consistent for each individual crop (except for Coffee and Tea). In addition, LCM, CA-Markov, and MCE used the Markov Chain model and the probability to change in the calibration stage was calculated from the rapidly changing quantity (see Section 3.3.1 of Chapter 3). This could explain why the possibility of Coffee and Tea in the simulations was inaccurate.

5.2 Lam Mun Sub-watershed (LMSW)

5.2.1 Comparison of correct/incorrect simulation maps for Lam Mun Sub-watershed

The binary maps of the correct and incorrect simulations were created from the reference map (2015) (Figure 5.5) and the projection maps from each model. The cells that show the incorrect simulation are shown in grey in Figure 5.6 and the correct cells are shown in black.

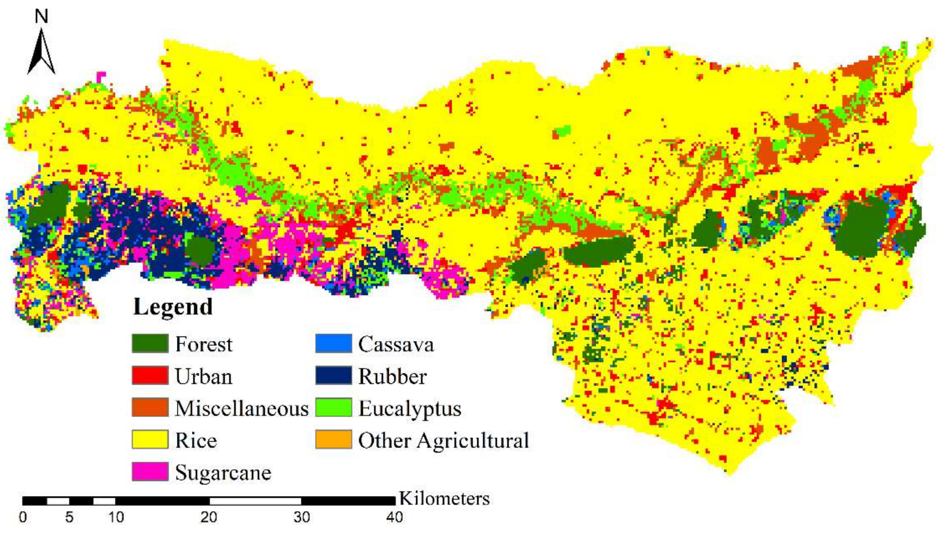


Figure 5.5 Land use map 2015 for LMSW

(a) Dyna-CLUE (76.8% correct)

(b) CA-Markov (83.4% correct)

(c) MCE (81.6% correct)

(d) LCM (89.4% correct)

(e) ABM (77.71% correct)

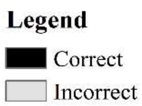


Figure 5.6 Correct and incorrect simulation maps for LMSW from Dyna-CLUE, CA-Markov, MCE, LCM, and ABM. Correct simulation shown in Black, incorrect simulation shown in Grey.

From Figure 5.6, it can be seen that all five models correctly simulate over 75% of the study area. The LCM binary map (Figure 5.6(d)) shows the largest area with correctly simulated land use (89.4%), while the Dyna-CLUE binary map (Figure 5.6(a)) shows the smallest area with correctly simulated land use (76.8%).

Considering the distribution of binary cells, some similarities can be observed across the models. Rice is well simulated by all the models. The largest land use category for LMSW is Rice (approximately 66% of the area in 2015) (Figure 5.5).

The binary map of Dyna-CLUE (Figure 5.6(a)) simulated the area in multiple land use categories in the west of LMSW very poorly. Dyna-CLUE simulated the contiguous areas of Rice well, but it simulated the Cassava areas poorly.

The LCM (Figure 5.6(d)) shows correct simulation across most of the area, but a small area of incorrect simulation occurred at the eastern edge of the sub-watershed, which is an area of mixed land use.

When comparing between the binary maps of CA-Markov (Figure 5.6(b)), MCE (Figure 5.6(c)), and ABM (Figure 5.6(e)), they also simulated areas with multiple land use categories poorly. These maps look similar in terms of the distribution of correct and incorrect cells, but the percentage of correct cells is slightly different.

Comparing all binary maps in Figure 5.6, the CA-Markov, MCE, LCM, and ABM maps all show a similar area of incorrect simulation that occurs in the south-west. CA-Markov and MCE simulated well the areas of Rice, Sugarcane and Eucalyptus, while LCM simulated well the areas of Rice and Eucalyptus. ABM only simulated well the areas of Rice. However, all models still did not simulate the area of mixed land use categories well and this area in the south-west was mixed between Sugarcane and Cassava.

The land use categories in the south-west are easy to change i.e., change from Rice to Sugarcane or Cassava (and are somewhat inter-changeable). In this area the suitability mapping (for different agricultural land use categories could not distinguish between the different crops (which have similar requirements). In addition, it is relatively easy for crops such as Sugarcane or Cassava to change between these crops or to another use, allowing these cells to change under simulation relatively easily. These factors likely combined to result in a low accuracy for Sugarcane and Cassava in particular. These factors made it difficult for any of the models to correctly simulate this region.

There is common agreement across some of the models for large parts of the study area. Figure 5.7 shows how many models correctly simulated each cell. Table 5.3 indicates the percent of times the cell was correctly simulated in each land use category, based on Figure 5.7.

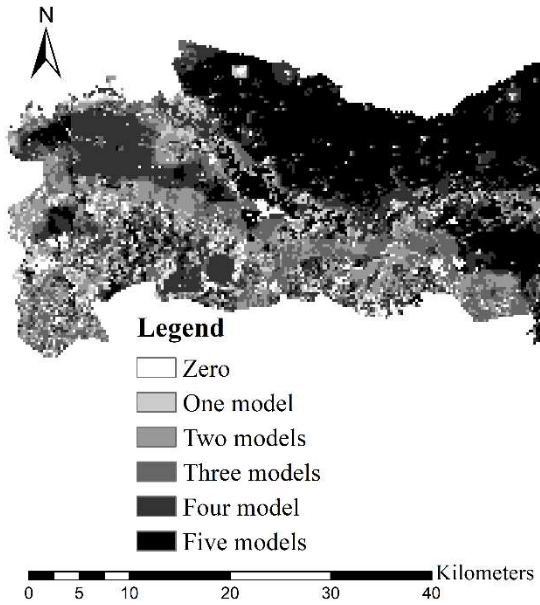


Figure 5.7 The number of times out of five that an individual cell was correctly simulated in LMSW.

Table 5.3 The number of times out of five that a cell was correctly simulated in any given land use category

Land use categories	Land use 2015 (cells)	Percent of cells correctly simulated					
		None	One	Two	Three	Four	Five
Rice	29,175	0.83	1.47	5.18	5.74	9.62	77.15
Miscellaneous	2,913	5.22	3.57	11.95	19.98	29.97	29.32
Eucalyptus	2,493	12.96	4.89	6.22	12.15	23.27	40.51
Urban	2,333	2.10	1.97	5.53	17.19	25.38	47.84
Forest	2,330	1.20	1.07	5.79	18.33	30.30	43.30
Rubber	2,182	22.32	12.33	12.60	17.69	26.63	8.43
Sugarcane	1,604	18.45	10.10	27.62	30.42	12.16	1.25
Cassava	650	54.15	12.00	23.08	9.08	1.38	0.31
Other Agricultural	258	34.11	18.22	29.46	17.44	0.78	0.00

Consistently accurate simulation from all models (darkest in Figure 5.7) occurred in the northern and eastern parts of the study area, corresponding to the main area of Rice production (77.15%). The distribution of Rice tends to be similar from year to year which makes it easier to simulate.

Correct simulation by four models (dark grey shading) mainly occurred around the central and north-west region (Figure 5.7) which consists mainly of Forest (CA-Markov, MCE, LCM, and ABM) (30.30%) (Table 5.3). Sugarcane cells were often simulated correctly by just three models (CA-Markov, MCE, and ABM). While the correct simulation from one, two, or three model mainly occurred around the south-west region. This is an area of mixed uses consisting of Rice, Sugarcane and Rubber (Table 5.3).

Incorrect simulations from all models (lightest shading) mainly occurred in regions where Cassava (54.15% incorrect) was present (Figure 5.7 and Table 5.3).

In the south-western part of the sub-watershed, it is easy for the Rice area to change to other land use categories, but it is also easy to change back to Rice (from Sugarcane or Cassava). Although Rice is a common land use and often does not change, the policy that encouraged farmers to change from Rice to Sugarcane or Cassava (Section 3.2.3 of Chapter 3) led to incorrect simulations as this could not be modelled easily. The elasticity of conversion figures for Rice, Sugarcane and Cassava were similar which meant there was little differentiation between the crops, while cells were relatively easy to change. All these factors led to relatively low accuracy for Sugarcane and Cassava.

The following section examines and compares the performance of each model in selected areas.

Given the variation across the study area, it was decided to focus on sample areas by selecting interesting areas (five blocks), to consider the performance of the models, within each focus area (at a detailed level). Figure 5.8 shows the correct and incorrect simulation blocks comparison in LMSW for the five selected focus areas.

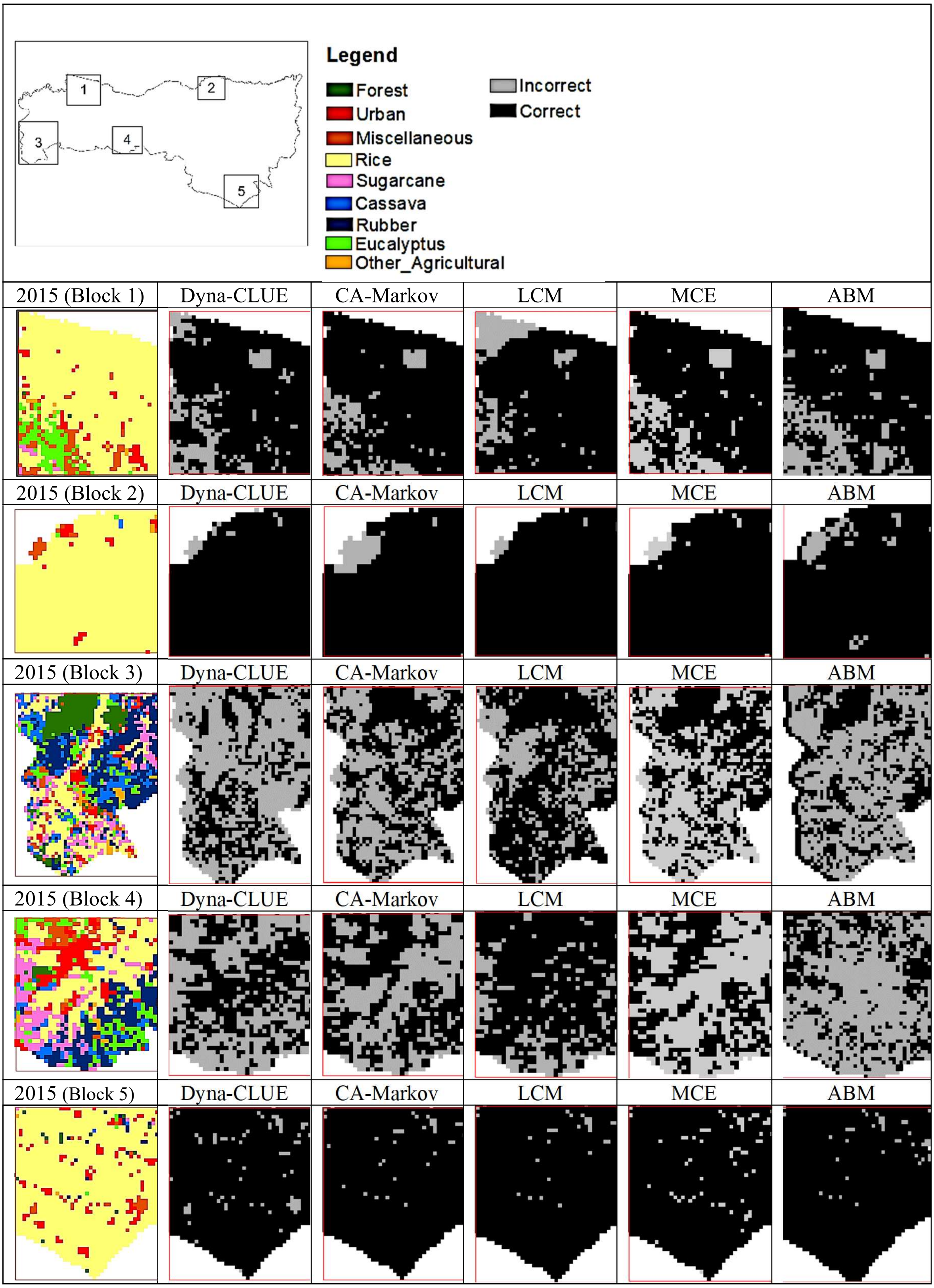


Figure 5.8 Correct and incorrect simulation blocks comparison in LMSW

The sample areas (Figure 5.8) provide evidence that the models work better where there are large blocks of a single land use. It is also notable that the heterogeneity of the block seems to be more important than the differences between the individual models (all models perform well where there is a large area of Rice and all models perform less well where there is heterogeneity).

The reference map 2015 (LMSW) of blocks 3 and 4 also show many categories of land use such as Urban, Rice, Sugarcane, Cassava, Rubber and Other Agriculture i.e., they are heterogeneous. These are clearly the worst simulated blocks in this study area across all models. The mix of different land uses is likely to be the reason Blocks 3 and 4 in LMSW are difficult to simulate well.

The next section analyses the detail of the accuracy assessment, using overall accuracy, user's accuracy, and producers' accuracy for Lam Mun Sub-watershed.

5.2.2 Accuracy assessment for Lam Mun Sub-watershed

The validation and accuracy of the land use simulation maps for LMSW, which were evaluated by overall accuracy, producer's accuracy and user's accuracy for LCM, CA-Markov, MCE, ABM, and Dyna-CLUE are shown in Table 5.4.

Table 5.4 Comparison of validation from LCM, CA-Markov, MCE, ABM and Dyna-CLUE in LMSW, ranking the models from highest to lowest overall accuracy (in percent)

Land use	*LCM*				*CA-Markov*				*MCE*				*ABM*				*Dyna-CLUE*			
	Producer's Accuracy	**User's Accuracy**	**Average of producer's and .**	**Ranks**	**Producer's Accuracy**	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**	**Producer's Accuracy**	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**	**Producer's Accuracy**	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**	**Producer's Accuracy**	**User's Accuracy**	**Average of producer's and user's accuracy**	**Ranks**
RIC	98	94	96	**2**	88	97	93	**1**	87	96	92	**1**	91	92	91	**1**	89	89	89	**1**
FOR	98	92	95	3	83	92	88	3	83	92	88	**2**	92	81	86	2	56	97	77	3
URB	97	97	97	**1**	87	97	92	**2**	84	93	88	**2**	100	81	91	**1**	83	72	78	**2**
MIS	88	82	85	4	80	74	77	4	70	65	68	3	50	62	56	3	66	50	58	5
EUC	75	68	72	5	78	53	66	5	74	50	62	4	59	48	54	4	64	54	59	4
RUB	48	78	63	6	62	59	61	6	58	56	57	5	43	50	46	5	19	48	34	6
SUG	29	48	39	7	72	36	54	7	69	34	52	6	24	42	33	6	19	21	20	7
CAS	17	35	26	**8**	32	31	32	**9**	31	29	30	**8**	14	16	15	**8**	4	8	6	**8**
OTH	9	19	14	**9**	52	34	43	**8**	44	29	37	**7**	25	10	18	**7**	2	1	2	**9**
Overall Accuracy (%)	**89**				**84**				**82**				**80**				**77**			

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, SUG= Sugarcane, CAS=Cassava, RUB=Rubber, EUC=Eucalyptus and OTH=Other Agricultural)

The overall accuracy for LMSW was greater than 80% for the LCM, CA-Markov, MCE, and ABM models (as shown in Table 5.2). LCM produced the highest overall accuracy, while Dyna-CLUE produced the lowest (77%).

LCM shows the highest overall accuracy with 89%. The user's accuracy ranged from 19% to 94%, while the producer's accuracy ranged from 9% to 98%. The broad range of accuracy indicates a severe confusion of Sugarcane and Cassava with other land use categories, and very poor simulation in the Other Agricultural category, contrasted with high accuracy in Rice, Forest and Urban. The users' accuracy indicates the number of correctly identified cells in a given class in the simulation map. Thus, Rice was found to be more reliable with user's accuracy of 96%.

Dyna-CLUE shows an overall accuracy of 77%. The user's accuracy ranged from 1% to 97%, while the producer's accuracy ranged from 2% to 89%. The broad range of accuracy indicates a severe confusion of land use categories similar to LCM (describes above). Which Dyna-CLUE showed a larger range than LCM.

The average of the producer's and user's accuracies was calculated, and the land use categories were ranked in order of accuracy. Taking the average of the producer's and user's accuracy for LCM, CA-Markov, MCE, ABM, and Dyna-CLUE in LMSW, the highest ranked categories are Rice, Urban, and Forest which are over 77% accurate across all models. On the other hand, Sugarcane and Cassava come out poorly in all the models with an average accuracy of less than 55% in each case.

Rice, Forest and Urban are well simulated in all models. The elasticity of conversion of Forest and Urban are more difficult to change than other land use categories, also Rice has low elasticity of conversion (described above, Section 5.1.2). Although the farmers have changed land use from Rice to field crops (e.g. Sugarcane and Cassava), it is not difficult to change back to Rice when the farmers are dissatisfied with the yield and benefit of the other crops.

Rice has a high producers' accuracy and users' accuracy of 98% and 94% respectively from LCM. This high value of the accuracies could result from the large expanse of Rice which tends not to change to other crops. This is reflected in the high user's accuracy which shows that 94% of the Rice in the simulation map was in the correct category. This could imply that the simulation map of Rice is sufficiently accurate. On the other hand, Cassava has a low producers' accuracy and users' accuracy of 17% and 35% respectively. Approximately 65% of the site identified as Cassava on the simulation map are actually in other agricultural land use categories on the ground. The overall confusion matrices for land use categories for all models can be seen in full detail in Appendix Tables 4.6-4.10.

In terms of the average of the producer's and user's accuracy from all models, when ranking from the most accurate category to the least, Rice (which ranges from 89-97%) is the most accurate category in every model except MCE (the most accurate category in MCE is Urban). Sugarcane (20-54%), Cassava (6-32%) and Other Agricultural (4-43%) are low ranking in all models.

In LMSW, all models simulate Rice and Urban very well but Cassava and Other Agricultural are poorly simulated. Looking at the producer's accuracy and users' accuracy for individual land use categories, all models show a high value for Rice, Forest and Urban. On the other hand, Cassava and Other Agricultural show a low value.

The results show that there was a large gap between producer's accuracy and users' accuracy in some of the models for individual crops such as Sugarcane and Cassava. In the models for this sub-watershed these two crops were often mis-classified as each other. The farmers' decision-making for Sugarcane and Cassava often depends on the crop's price and, pest problems (which can vary from year to year). Sometimes the farmers switch between these crops depending on climatic conditions or the crop's fluctuating value in the world market. This can explain the confusion between these categories.

In LMSW, Rice, Forest (and Urban) were considerably better than the other categories and performed quite well in both producers' and users' accuracies. On the other hand, the lowest ranking land uses (Other Agricultural, Cassava and Sugarcane) are similar across all models. For Rubber, CA-Markov, MCE, LCM and ABM have producers' and users' accuracies that are moderately good (higher than 50%), while the accuracies for this land use in Dyna-CLUE were quite low (producers' accuracy 19%).

5.3 Comparison between study areas and selection of models for simulations (2025)

Sections 5.1 and 5.2 presented comparisons of correct/incorrect simulation maps and the accuracy assessment for each study area. This section compares these evaluations across study areas and ultimately recommends the models which should be used for the simulation for 2025.

Table 5.5 indicates that the overall accuracies in LMSW (77-89%) (Table 5.5) were higher than in MCSW (63-77%). The shading in the table is based on the value of the overall accuracy (highest in dark green to lowest in white shading). From the results in previous sections, it is clear that these differences were driven by a big range in accuracy between the simulation of different land use classes with some simulated well (e.g. Rice Urban and Forest), and some simulated very poorly (e.g. Cassava and Other Agricultural).

Table 5.5 Comparison of overall accuracy from LCM, CA-Markov, MCE, ABM and Dyna-CLUE between MCSW and LMSW

Study areas	Overall Accuracy (%)				
	LCM	CA-Markov	MCE	ABM	Dyna-CLUE
MCSW	77	75	74	66	63
LMSW	89	84	82	80	77

It is important to note that the relative order of the models is the same in both study areas. In MCSW three models (LCM, CA-Markov, and MCE) stand out as better than the other two (ABM and Dyna-CLUE). However, in LMSW there is more of a gradation. The models generally perform better in LMSW than in MCSW, even though LMSW has less variation in environmental conditions. This reflects the dominance of certain types of crop which are simulated better, leading to a higher overall accuracy. This can be seen when the amounts of the different land uses are compared. For instance, Rice covers 63.9% of LMSW as compared with 16.0% of MCSW (Section 3.3 of Chapter3).

LCM and CA-Markov are the first and second best in both study areas (in terms of overall accuracy) (Table 5.5), while Dyna-CLUE shows the lowest overall accuracy. This can inform the choice of models for the simulation stage that is discussed in the following section.

Considering which models should be used for the simulation

The land use transition probability in each model was generated from historical maps (e.g. Dyna-CLUE and CA-Markov). The results of the validation show that the Dyna-CLUE performs less well, and some crops are very poorly simulated in each study area. Dyna-CLUE used the maps of past land use for demand calculation i.e. the trend of each land use category over nine years. The land transitions in Dyna-CLUE are partially determined by the conversion elasticity settings of the land uses. The reason Dyna-CLUE performed less well than the other models could be because the conversion elasticity settings did not capture the type of change which was occurring in the real world. The same values were used in both study areas, but there may be local differences (the Forest areas seem to be less vulnerable to encroachment in LMSW for example). Dyna-CLUE can be effective where the historical trend continues, but it cannot respond to factors which are outside the model which might change the historical trend (e.g., changes in market price or policy).

Dyna-CLUE was the least accurate model in both study areas thus Dyna-CLUE was not selected for the simulation stage of this study. Dyna-CLUE has been used effectively in previous studies which focus on deforestation and urbanisation (Akber and Shresta, 2015; Boonchoo, 2015; Losiri et al., 2016; Chavanavesskul and Cirella, 2020). From the evidence of this study, Dyna-CLUE does not seem to be such an effective tool for studying trends within individual agricultural land uses.

Considering the other choices of model, the best overall simulation was from LCM, though the overall accuracy score hides large differences in accuracy between individual land uses, CA-Markov was the second-most accurate model in both study areas and MCE was the least accurate stochastic model. The accuracy assessment of CA-Markov shows that the model performed reasonably well in both study areas. Looking at the stochastic models, the CA-Markov module in IDRISI is a basic function that is not complicated to apply (in terms of data collection and application) and requires only the historical maps (for input data), while LCM and MCE are more sophisticated models.

The MCE was slightly less accurate than the CA-Markov in both study areas. This might be considered a surprising outcome as it is a more sophisticated model, but one possible cause could be the weights which were applied to the variable factors (which determine the location of change). The same weights were applied to both study areas based on reasonable assumptions about the importance of each factor. There may however be local differences or variations which are not reflected by the given weights, which could account for the inaccuracy. The results imply that the weights do not fully reflect the observed transitions, and this is possibly the reason that the MCE is less accurate than the CA-Markov.

LCM incorporates an element of machine learning. It is able to empirically model the relationship between land cover transitions and independent variables and is therefore more sophisticated than a basic CA-Markov (which only uses the historical trend). This could explain why the LCM is more accurate than the CA-Markov in both study areas. LCM was selected for the simulation stage as it was the most accurate model in the validation stage. It was also decided to include CA-Markov in the simulation stage as it was reasonably accurate and is interesting to include for the purpose of comparison (to see if more sophisticated models do better or not). The MCE models generally performed slightly less well than LCM or CA-Markov so there did not appear to be any additional benefit in using them for simulations.

ABM presents a different type of simulation method, incorporating the farmers' decision making as a filter in the model, as well as applying the suitability map from MCE (Section 4.3.2 of Chapter 4) in calibration setup (Section 4.4 of Chapter 4). It might be expected that the ability to incorporate human decision making would lead to a more accurate model (than the CA-Markov for example) but this was not found to be the case. The difficulty with ABM is finding and incorporating sufficient empirical data on the decision making of individual agents. The reason that the ABM has not performed better is probably because of the parameterisation of the model (particularly the use of a single set of weights and associated suitability model from the MCE) and the sample size (which was a sample of 50 farmers for each study area). Another factor is that each village can have a different culture, particularly within the mountain areas, and plain agriculture is different for mountain agriculture in Thailand. Previous researchers have also found that it is difficult to apply an ABM at larger scales (Walsh et al., 2013; Beckers et al., 2018). Despite the difficulties the ABM incorporates the element of human behaviour, and the ABM is therefore interesting to include in the next stage, as well as the LCM and CA-Markov models.

5.4 Summary

This chapter has examined the performance of five models. The comparison examined distributions of correct/incorrectly simulated cells, and accuracy assessment (by producers', users', and overall accuracies).

The overall accuracies were higher in LMSW (77-89%) than in MCSW (63-77%). From the results it is clear that there is a big range in accuracy between the different land use categories with some simulated well, and some simulated very poorly. The reason that the accuracies are higher in LMSW could be attributed to the fact this area has a large amount of Rice, which is moderately stable. This leads to high accuracy for simulation of Rice and high overall accuracy.

There are considerable differences in environmental factors between the sub-watersheds, such as slope which can influence the characteristic crops and land uses. The study provides some evidence that environmental factors influence the distribution of different land uses. Although there is less variation in slope in LMSW there are subtle variations in the environment which could be important. Plain areas (0-2% slope) tend to be dominated by Rice, while the slightly higher ground (2-5% slope) is favored by the farmers for field crops such as Sugarcane and Cassava as these areas are unlikely to flood. This means that environmental factors can still be effective in simulating the distribution of crops within LMSW.

For the simulation stage in the next Chapter, the selected models are: LCM, CA-Markov, and ABM. LCM and CA-Markov have been chosen to represent the stochastic models for the simulation stage as these were the most accurate models. Both modules can be run in IDRISI (TerrSet). LCM performed well in validation and is a specific module in IDRISI. The CA-Markov module (in IDRISI) also performed well in the validation (it was the second-most accurate model). The CA-Markov module can be considered a basic model, which has been selected for the simulation stage to compare with other (more complex) models.

The ABM model is representation of the process-based model type that uses the terms of decision making from farmers to drive the model. It is important to include this model in the next stage to see if this function improves the simulation or not. The Dyna-CLUE model performed least well of all five models in terms of validation and has therefore not been considered further.

A comparison of the models' output performance and reliability is presented in Chapter 6.

Chapter 6 | Simulation of agricultural land use

6.1 Introduction

Following reasonable performance in tests for accuracy assessment, three land use models were used to simulate future land use. The purpose of this chapter is to analyse and compare the results from the different models and draw conclusion on the following research questions: what are the possible simulated future land use changes? And, are some types of model better than others for predicting (certain types of) land use change? Specifically, the discussion will address the simulations from the different models, the extent to which the simulations from the different models agree or disagree, how simulations compare with observed data, and finally, how simulations compare with the understanding(s) of local experts.

Analysis herein is informed by the accuracy assessment from Chapters 5, which consisted of a two-stage approach (calibration and validation) comparing five different models. All of the models provided predictions which were classified as good to excellent (overall accuracy between 66-68%) and three models were chosen based on a combination of the validation accuracy they achieved and their representation of different types of models. See Section 5.5 for more details.

These models were a combined Markov and Cellular Automata (CA-Markov) (which operates in TerrSet by IDRISI), a combined Markov and Cellular Automata with factor variables (Land Change Modeller (LCM) in TerrSet by IDRISI), and an Agent Based Model (ABM) (using NetLogo) (for a detailed description of the models see Chapter 4). This chapter now describes the simulation outputs which were produced using CA-Markov, LCM and ABM.

Once the validity of these models was assured for 2015/16, maps of land use for 2025 could be simulated. It was decided that the most appropriate period of time to simulate for this study would be 10 years into the future, starting from the last validation year (2015/2016). The reasons for this were as follows. Most local policies, such as the watershed development plan and agricultural development plan are set for 5 or 10 years (Chapter 3). If the model simulates only the next five years, it would be a short period of time and significant change would be unlikely to occur. On the other hand, if the model simulates the next 15-20 years

(2030-2035) there are many additional factors which could impact on the simulation such as government policy, disaster, and pests, as well as climate change.

Moreover, this thesis has been undertaken during the period of 2016 to 2020. The year 2025 was chosen as the simulation year as it was originally 10 years from the last observed data set. Since the beginning of the thesis, however, a further observed data became available for the year 2018/19, which is almost halfway through the simulation period. The data for 2018/19 can confirm or cast doubt on the trends which are simulated in the models. The data for 2018/19 can also be used as an additional evaluation point for assessing the accuracy of the models. Thus, each model was used to simulate the land use in 2025 and the trends were compared with the observed data for 2018/19.

Simulations were also processed for two study areas: Mae Chan Sub-watershed (MSCW) and Lam Mun Sub-watershed (LMSW), because of their different characteristics. The topography of MCSW consists of hills and plain. Forest is the most extensive land use in this area (41.43%) while the largest agricultural land uses are Maize and Rice. On the other hand, the LMSW is relatively flat with some undulating landform. The largest land use category in this area is Rice (66.28%), which cover a majority of the area. The total area of LMSW is 276,975 hectares, more than double the size of MCSW (125,777 hectares). See Chapter 3 for further details of the study areas.

This study also sought the opinion of local land use experts. A total of six individual experts were questioned. Two experts (No.1 and No.2) answered for both study areas, two answered only for MCSW (No.3 and No.4) and two only for LMSW (No.5 and No.6). The local land use experts in each area were asked what they thought the likely trend in each crop would be over the next 10 years (they were asked if they thought each crop would increase, decrease or stay the same). The outputs of the simulation could then be compared with the opinion of the experts to see how the projected tendency in each of the agricultural crops compared with the expectation of the local experts. Based on the validation and simulation outputs, and a discussion of the ease of the application, the experts were also asked to give their opinion on the relevance of the different model approaches to their work, how the models might fit with their work and how easy the models would be to apply. On this basis, the experts were asked to score each model (on a scale of 1-9 with 1 being the least suitable and 9 the most suitable). More detail about the survey of expert opinion is provided in the data preparation section (see Chapter 4).

This chapter deals with the simulation of land use categories within MCSW (Section 6.2) and LMSW (Section 6.3). For each study area, the outputs of the simulations of land use in 2025 from the three models (CA-Markov, LCM and ABM) are presented, followed by an evaluation of the simulation outputs by spatial distribution, comparison with the observed data (from 2018/19) and comparison with the expectations of local experts. Section 6.4 presents a further comparison of the simulation outputs for the agricultural land use categories between both study areas and between the models. Section 6.5 discusses the overall performance of land use models and the chapter concludes in Section 6.6 with answers to the research questions posed above.

6.2 Mae Chan Sub-watershed (MCSW)

6.2.1 Simulation of agricultural land use in 2025 for Mae Chan Sub-watershed

Following model validation for 2016 (see Chapter 5), land use in MCSW was simulated for 2025. In terms of the total amount of land use change within this study area the models simulated that 7,179 hectares (5.90%), 7,615 hectares (6.05%) and 19,567 hectares (17.60%) from CA-Markov, LCM and ABM, respectively would change use between 2016 and 2025. A summary of the simulation outputs is presented in Table 6.1.

Model simulations show land use change between the baseline year (2016) and the simulation year (2025), with a net increase or decrease in each category (Table 6.1). Ordered from the category with the greatest overall change (absolute value) the land uses are: Maize (decrease), Rubber (increase), Pineapple (increase), Other Agricultural (decrease), Coffee and Tea (increase), Urban (increase), Rice (decrease), Miscellaneous (decrease), and Forest (decrease), respectively.

Table 6.1 Simulated land use change between 2016 and 2025 in Mae Chan Sub-watershed (MCSW)

Land use	2016 (%)	2025 (%)			%Change (2025)			Average %change
		CA-Markov	LCM	ABM	CA-Markov	LCM	ABM	
Maize	18.01	16.57	16.70	12.88	-1.44	-1.31	-5.13	↓ -2.63
Rubber	3.91	6.25	6.10	3.83	2.34	2.19	-0.08	↑ 1.54
Pineapple	2.26	2.81	2.77	5.38	0.56	0.51	3.13	↑ 1.40
Other Agricultural	6.81	6.14	5.86	4.71	-0.67	-0.95	-2.10	↓ -1.24
Coffee and Tea	3.76	3.71	3.70	7.18	-0.05	-0.06	3.41	↑ 1.18
Urban	4.62	4.67	4.73	6.88	0.05	0.11	2.26	↑ 0.80
Rice	15.73	15.54	15.56	14.65	-0.19	-0.17	-1.08	↓ -0.48
Miscellaneous	3.47	2.87	2.93	3.30	-0.60	-0.53	-0.16	↓ -0.43
Forest	41.43	41.43	41.65	41.18	0.00	0.22	-0.25	↓ -0.16
Total	**100**	**100**	**100**	**100**	**5.90**	**6.05**	**17.60**	**9.85**

All models show an increasing trend in the area of Pineapple and Urban. Conversely all models show a decreasing trend in the area of Maize, Rice and Other Agricultural within this study area. For other land uses there is little consensus between models, for example, the simulation of Rubber and Coffee and Tea from CA-Markov, LCM and ABM show different trends. The results from CA-Markov and LCM show an upward trend in Rubber while the ABM simulates a downward trend. Conversely, the results from CA-Markov and LCM show a stable trend in Coffee and Tea whilst the ABM has an increasing trend in Coffee and Tea.

There is quite a high level of agreement between CA-Markov and LCM across the agricultural land use categories. The ABM, on the other hand, produces a set of results which are quite different from the other models. The ABM for example suggests a large decrease in the area of Maize while the other models suggest a smaller decrease.

Tables 6.2-6.4 show cross-tabulation of the simulation outputs and the baseline map for each model. These tables indicate the particular changes between land use categories that are being simulated and allow an assessment of whether the shifts are concentrated in a small number of categories or more widely spread. Looking at the overall results from the different simulations, it is quite noticeable that there is little movement between land use classes in

CA-Markov (Table 6.2) but a lot of movement between classes in the ABM (Table 6.4). Indeed, changes in the ABM output occurred between almost all categories, except Urban. LCM is intermediate between the CA-Markov and ABM in terms of transition between crops.

Table 6.2 Cross-tabulation comparing the area (in percent) of land use in 2016 (column) to the simulation for 2025 (row) for CA-Markov in MCSW

Land use		**Land use 2016**									**Total**
		FOR	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**	**2025**
Simulation 2025	**FOR**	41.43	-	-	-	-	-	< 0.001	-	-	**41.43**
	URB	-	4.62	0.05	-	-	-	-	-	-	**4.67**
	MIS	-	-	2.79	-	0.08	-	-	-	-	**2.87**
	RIC	-	-	0.17	15.30	< 0.001	-	-	-	0.06	**15.54**
	MAI	-	-	-	-	16.57	-	-	-	-	**16.57**
	PIN	-	-	0.05	0.29	0.39	1.94	-	-	0.15	**2.81**
	COF	-	-	-	-	0.05	0.05	3.61	-	-	**3.71**
	RUB	-	-	0.40	0.13	0.47	0.27	< 0.001	3.91	1.06	**6.25**
	OTH	-	-	-	< 0.001	0.45	-	0.15	-	5.54	**6.14**
Total 2016		**41.43**	**4.62**	**3.47**	**15.73**	**18.01**	**2.26**	**3.76**	**3.91**	**6.81**	**100**

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, PIN= Pineapple, COF=Coffee and Tea, RUB=Rubber, OTH=Other Agricultural)

Table 6.3 Cross-tabulation comparing the area (in percent) of land use in 2016 (column) to the simulation for 2025 (row) for LCM in MCSW

Land use		**Land use 2016**									**Total**
		FOR	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**	**2025**
Simulation 2025	**FOR**	41.43	-	-	-	0.04	-	0.06	-	0.12	**41.65**
	URB	-	4.62	0.04	0.02	0.03	< 0.001	0.01	-	< 0.001	**4.73**
	MIS	-	-	2.74	< 0.001	0.06	0.07	-	-	0.07	**2.93**
	RIC	-	-	0.17	15.11	0.01	-	-	0.01	0.25	**15.56**
	MAI	-	-	0.01	-	16.29	0.01	0.05	-	0.33	**16.70**
	PIN	-	-	0.10	0.27	0.40	1.71	-	0.11	0.18	**2.77**
	COF	-	-	-	-	0.10	0.10	3.49	-	0.01	**3.70**
	RUB	-	-	0.34	0.11	0.42	0.34	0.04	3.73	1.12	**6.10**
	OTH	-	-	0.07	0.22	0.65	0.02	0.12	0.06	4.72	**5.86**
Total 2016		**41.43**	**4.62**	**3.47**	**15.73**	**18.01**	**2.26**	**3.76**	**3.91**	**6.81**	**100**

Table 6.4 Cross-tabulation comparing the area (in percent) of land use in 2016 (column) to the simulation for 2025 (row) for ABM in MCSW

Land use		**Land use 2016**									**Total**
		FOR	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**	**2025**
Simulation 2025	**FOR**	36.97	-	0.16	0.54	1.90	0.17	0.36	0.26	0.82	**41.18**
	URB	0.41	4.62	0.12	0.99	0.27	0.07	0.04	0.07	0.28	**6.88**
	MIS	0.15	-	2.09	0.31	0.23	0.20	<0.001	0.12	0.20	**3.30**
	RIC	0.47	-	0.28	12.04	0.68	0.25	0.03	0.27	0.64	**14.65**
	MAI	1.48	-	0.22	0.65	8.92	0.07	0.09	0.21	1.24	**12.88**
	PIN	0.62	-	0.29	0.40	2.15	1.27	0.02	0.30	0.33	**5.38**
	COF	0.57	-	0.05	0.16	3.08	<0.001	3.14	0.05	0.12	**7.18**
	RUB	0.23	-	0.18	0.27	0.28	0.15	0.01	2.52	0.19	**3.83**
	OTH	0.53	-	0.09	0.36	0.51	0.07	0.06	0.12	2.97	**4.71**
Total 2016		**41.43**	**4.62**	**3.47**	**15.73**	**18.01**	**2.26**	**3.76**	**3.91**	**6.81**	**100**

Land use perspective

While Table 6.1 shows changes in crops across the study area, Tables 6.2-6.4 show simulated movement between crops. Pineapple, for example, shows an increase in all models. The simulation of land use using LCM shows that the area of Pineapple will increase by 0.51% (the increased area will mostly replace Maize or Rice, Table 6.3). The CA-Markov also simulates an increase in Pineapple of 0.56% and again, most of the increase in the area of Pineapple would be due to decreases in Maize or Rice (Table 6.2). The ABM simulation suggests a larger increase in the amount of Pineapple of 3.13%, with a corresponding reduction in the area of Maize or Rice (as a result of conversion to Pineapple) (Table 6.4).

The simulations from CA-Markov and LCM suggest that the area of Urban will be relatively stable (Table 6.1). The ABM on the other hand suggest that the Urban area will expand quite noticeably by 2.26%. In this simulation Urban mainly replaces areas which were previously Rice, Maize or Forest (Table 6.4).

All the simulations show a downward tendency in the area of Maize (Table 6.1). Using CA-Markov, the simulation suggests that the area of Maize area will decrease by 1.44% with the reduction mostly being due to reallocation to Pineapple, Rubber or Other Agricultural (Table 6.2). Using ABM, Maize will reduce by 5.13% with the reduction mostly being due to reallocation to Pineapple or Coffee and Tea (Table 6.4). The simulation of land use using LCM, suggests a decrease in Maize of 1.31%, with most of the reductions in the area of Maize being due to increases in Rubber and Pineapple (Table 6.3).

The simulated outputs for Rice suggest that this crop will see a small decrease of 0.17%, 0.19% or 1.08% using LCM, CA-Markov, and ABM, respectively (Table 6.1). The CA-Markov and LCM simulations show that most of the reallocation is to Pineapple (Table 6.3 and Table 6.2), while the ABM suggests reallocation primarily to Urban (Table 6.4).

The Other Agricultural area will see a decrease of 0.67%, 0.95% or 2.10% using CA-Markov, LCM or ABM, respectively (Table 6.1). The Other Agricultural category is made up of various small-amount crops such as Lychee, Longan, Oranges and Cassava. In the CA-Markov model, most of the reduction would be due to land being allocated to Rubber (Table 6.2). LCM shows that a majority of the reductions in the area of Other Agricultural would be due to increases in Rubber and Pineapple (Table 6.3). The ABM simulation shows that reduced areas of Other Agricultural will largely be replaced by Maize (Table 6.4). The percentage of decline in the area of Other Agricultural in this model is noticeably larger than CA-Markov and LCM (Table 6.1).

There is a relatively large increase of 2.19% and 2.34% in the Rubber area when using LCM and CA-Markov (Table 6.1), most of this increase being due to land which is reallocated from Maize and Other Agricultural (Table 6.3 and Table 6.2). However, the ABM simulation for 2025 shows that the amount of Rubber will be relatively stable (with a decrease of 0.08%).

The Coffee and Tea simulation outputs for 2025 from CA-Markov and LCM show that the extent of this crop is barely altered when compared with 2016 in this study area. On the other hand, the ABM suggests an enlargement by 3.41% (from 3.76% to 7.18%) (Table 6.1).

Model perspective

ABM is clearly different from CA-Markov and LCM in terms of the magnitude of simulated land use change, though there is general agreement about the direction of change. The previous paragraphs have described in detail the simulated changes in each land use and have considered the degree of agreement between the models (a land use-perspective). In practice, a land use modeler would select only one model from which to run a simulation. The following paragraphs consider the consequences of such a decision, i.e. the simulations from the perspective of individual models (a model-perspective).

The CA-Markov simulates an upward trend in the overall area of agricultural land, with agricultural land replacing land which was previously in the Miscellaneous category (Table 6.2). The land use which is expected to change the most is Rubber, which would expand from 3.91% to 6.25% of the total area (Table 6.1). There would also be a slight increase in the area of Pineapple (from 2.26% to 2.81% of the total area). The extent of Tea and Coffee, on the other hand would be stable (decreasing from 3.76% to 3.71% Table 6.1).

LCM simulates a similar increase in the overall area of agricultural land. The largest simulated change is again in Rubber (which is expected to increase from 3.91% to 6.10%) (Table 6.1). There would also be a slight rise is the area of Pineapple from 2.26% to 2.77% of the total area. The extent of Tea and Coffee on the other hand would be stable (decreasing from 3.76% to 3.70% of the total area according to this model).

The ABM also simulated a total increase in the area of agricultural land, but in this case, it would be due to a reduction in the area of Forest (Table 6.4). The simulation suggests that the area of Rubber would slightly decrease from 3.91% to 3.83% (Table 6.1). The area of Pineapple is expected to increase from 2.26% to 5.38% of the total area and there would be a substantial increase in the area of Coffee and Tea from 3.76% to 7.18% of the overall area according to this model (Table 6.1).

This section has looked at non-spatial changes i.e. the quantity of change in each category (and also the transformations between categories). To select a model, it is necessary to evaluate how probable the simulations are. One technique to evaluate the plausibility of the models is to look at the spatial distribution of the simulated changes and to use knowledge of the area to assess whether they are likely or not. This is addressed in the following section.

6.2.2 Evaluating the model simulations for the Mae Chan Sub-watershed

The following section evaluates the outputs from the models in a number of different ways. The simulation outputs produced using CA-Markov, LCM and ABM models in MCSW (described in Section 6.2.1 above) are firstly analysed in terms of the spatial distribution of land uses. Secondly, the simulation outputs are compared with the observed data for 2018/19 to help assess the accuracy of the simulations in relation to how the amount of each land use changed over time i.e., the trend. Thirdly, the trend for each crop is compared with the expectations of the local land use expects to see if they agree or not.

6.2.2.1 Evaluation of the spatial distribution of the outputs

Simulation outputs, from each of the three models, are spatially explicit, and can thus also be mapped. Simulations of land use in 2025 for all models are presented in Figure 6.1, for comparison against observed land use in 2016 (Figure 6.1(a)).

All three of the simulations show slightly different patterns of change from the initial map (Figure 6.1(a)). CA-Markov produces a very clumped pattern of change (Figure 6.1(b)) while LCM produces quite a scattered pattern of change (Figure 6.1(c)). ABM is the intermediate between CA-Markov and LCM (Figure 6.1(d)).

The LCM simulation map (Figure 6.1(c)) shows a scattered distribution of different land uses in the west of MCSW, and the zone of forest in the north-west corner of the study area has changed to agricultural land categories in this simulation. The map from CA-Markov (Figure 6.1(b)) shows land use changes which appear to be geographically clustered, while those from LCM and ABM show more dispersed distributions of changes (Figures 6.1(c) and 6.1(d)).

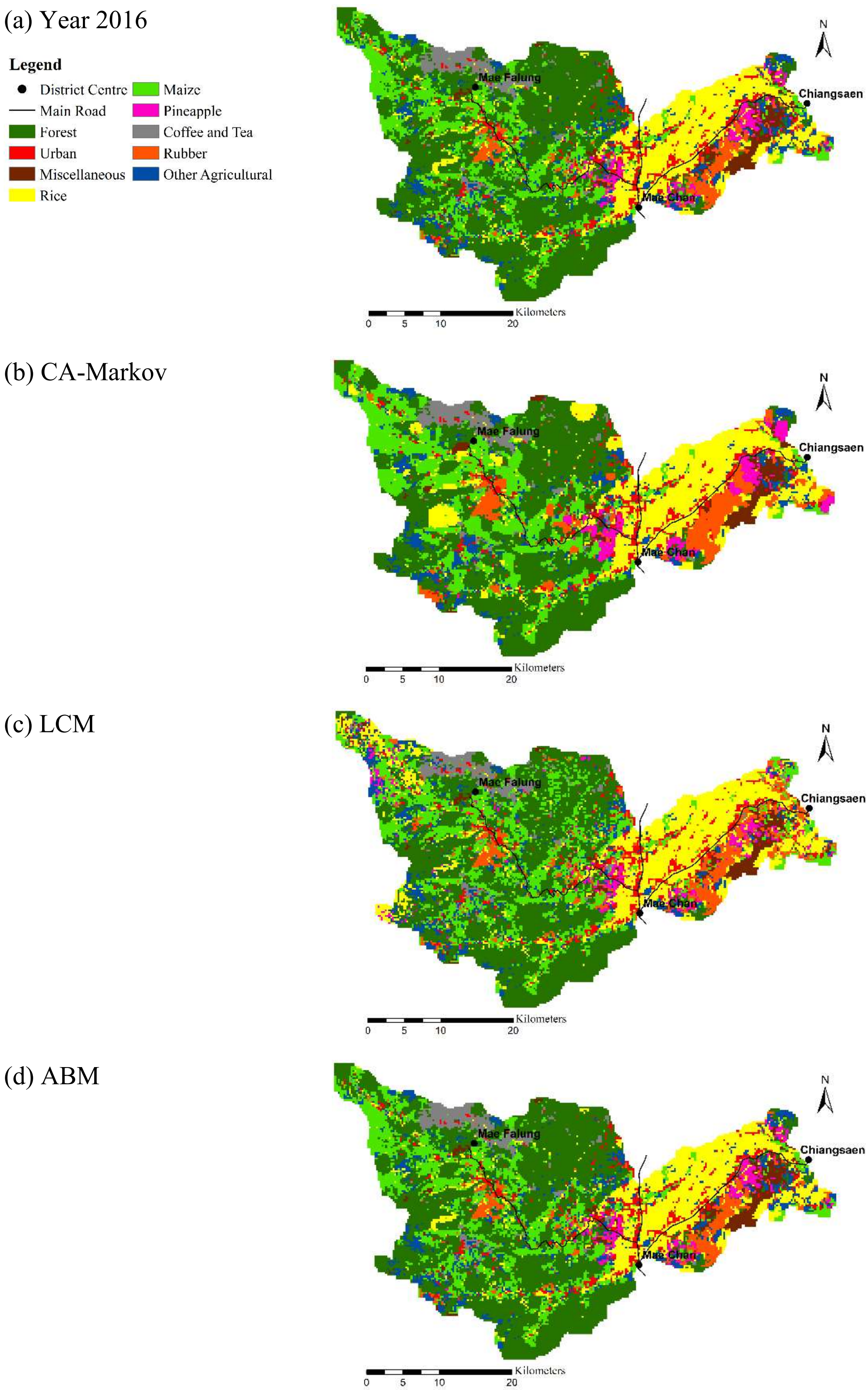


Figure 6.1 Land use in MCSW (a) 2016 and simulated land use in 2025 using (b) CA-Markov, (c) LCM, and (d) ABM

Simulation of land use for 2025 from CA-Markov is implausible because, despite expected increases in some crops (such as Maize and upland Rice, see Shutidamrong, 2004) expansion of agriculture is significant within the restricted forest area (these areas consist of high steep mountains with slopes greater than 35 degrees that are reserved for forest). A clustered distribution is likely an artefact of model design when land use change occurs near to existing areas of a particular agricultural land use type in the baseline year (2016) because of the neighbourhood rule.

The LCM simulation in Figure 6.1(c) and that for ABM in Figure 6.1(d) show patterns of change which are not clustered like those in CA-Markov (Figure 6.1(b)), and some of the land use categories have a more widespread or scattered distribution. LCM and ABM include driving force variables, such as soil fertility and slope in the models (see Chapter 3). These models include not only consistent land use change and transition rules, but the models have a suitability calculation for different land use types, which is used to simulate the future. This means that results are more likely to reflect the underlying variation within the environment (the environment of MCSW is heterogeneous particularly with respect to topographical variation).

LCM is also based on transition probabilities and applies a spatial suitability weighing to the driving forces to determine development in the land use categories. Thus, LCM has the ability to apply rules through a conversion process where the approximated change is not random (see more detail in Sections 2.2.2 and 4.3.3).

ABM, on the other hand, is a dynamic model where the simulation output is a result of the decision making of agents. In this model farmers' behaviour plays the role of governing the agents' activities (the agents in this model are the individual farmers – who are the effective decision makers). In other words, ABM uses the character and behaviour of the individual farmer in combination with behaviour of the neighbouring farmers to develop a land use map.

The spatial distribution of changes within each model can be further highlighted using binary change/ no change maps. The spatial distribution of the simulated land use changes between 2016 and 2025 from CA-Markov, LCM and ABM are shown in Figures 6.2 (a), 6.2 (b) and 6.2 (c) respectively.

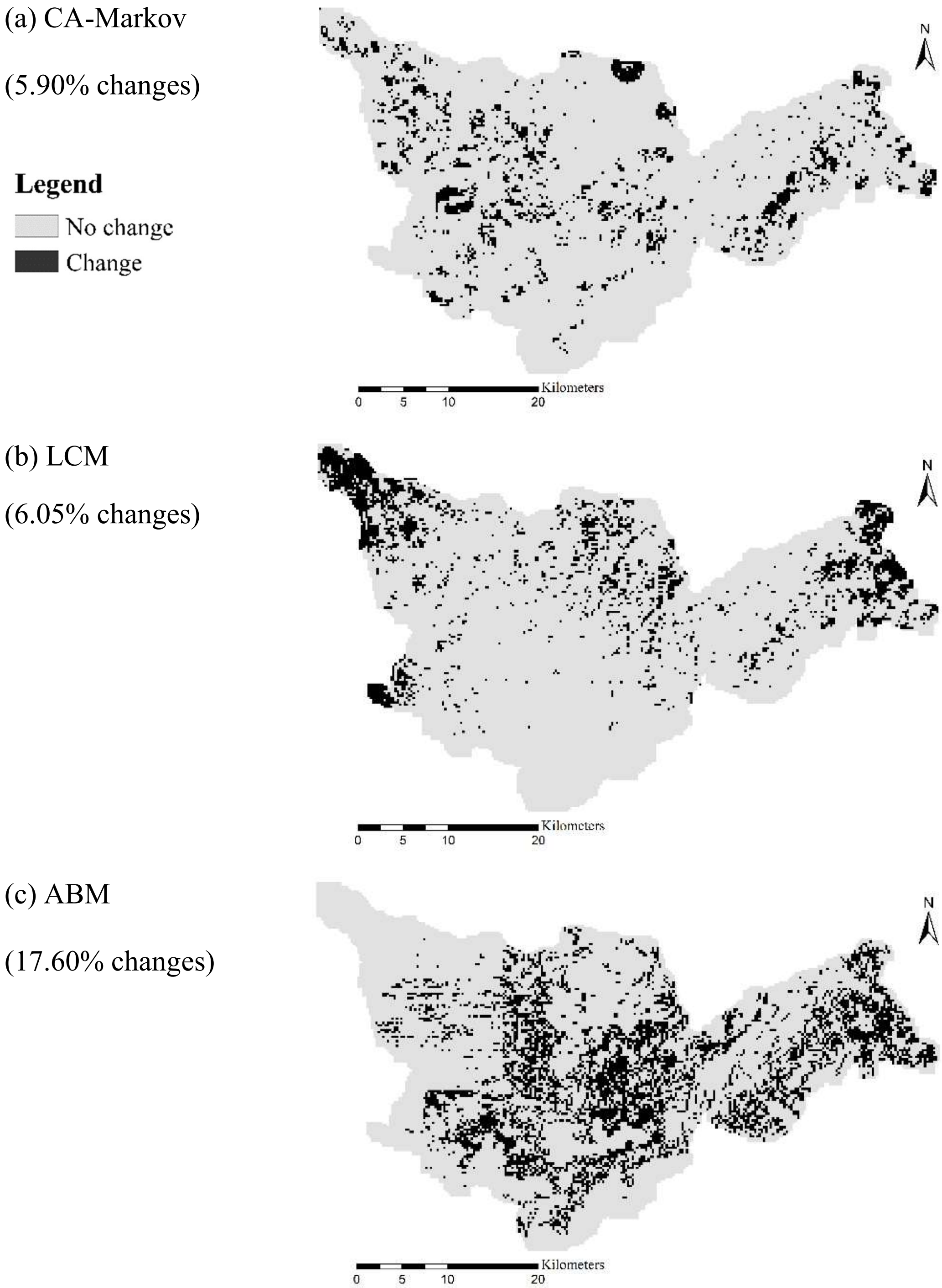


Figure 6.2 Changes in land use from 2016 to 2025 as simulated by (a) CA-Markov, (b) LCM and (c) ABM models of MCSW

As might be expected from the aggregated results of total land use change (Table 6.1), the simulated change area for ABM is substantially larger (17.60%) than those for CA-Markov (5.90%) and LCM (6.05%). It can be seen immediately from the maps that the distribution of change varies greatly across the models. The binary maps show that the changing areas occur in distinct clusters, but these clusters are located across the different models.

The binary map for CA-Markov (Figure 6.2 (a)) shows that change occurred primarily in the middle and the east (with two noticeable clumps to the south of the main road of the eastern part) and with a clump in the north. The greatest areas of change appear to be associated with the expansion of Rice (Figure 6.1 (b)). Clustering may be due to the influence of the neighbourhood effect. In a Cellular Automata, the land use changes for any location are influenced by the existing state and changes in adjoining cells, so the neighbourhood effect is very strong (Section 2.2.2 of Chapter 2).

The CA-Markov is a stochastic model. The CA-Markov technique uses the characteristic of probability transition from the historical map and the neighbourhood spatial association of pixels to simulate the future land use pattern. For example, the auto-allocation for the expansion in the area of Pineapple means that it is often allocated next to Pineapple that is already present. Furthermore, the CA-Markov model does not allow a hard restriction area such as protected forest, and this is a limitation of the model.

The simulation changes for LCM (Figure 6.2 (b)) shows that the majority of land use changes occurred in the north-west, with another clump in the west, another clump towards the eastern edge (around Chiangsaen district), and barely any change in the middle of the study area. Again, there appears to be a lot of change to Rice in the west. Other transitions are more dispersed and less easy to spot through visual examination.

LCM is also based on transition probabilities and applies a spatial suitability weighing to the driving forces to determine development in the land use categories. Thus, LCM has the ability to define the application of the rules by using a conversion rule where the approximated change is not random (see more detail in Sections 2.2.2 and 4.3.3).

Changes simulated by ABM (Figure 6.2 (c)), were dispersed across the entire study area, with the exception of the extreme north-west and western areas. LCM and ABM therefore simulate change occurring in very different locations.

ABM is a dynamic model where the simulation output is a result of the decision making of agents. In this model farmers' behaviour plays the role of governing the agents' activities (the agents in this model are the individual farmers – who are the effective decision makers). In this study, the ABM includes the character of the individual agents which act as a filter to influence whether change takes place i.e. change only in occurs places where farmers are willing to change (see Section 4.4 of Chapter 4).

Performing a visual comparison of simulation maps output emphasises how differently the models are behaving over space. Whilst it could be seen from the cross-tabulation data (Tables 6.2-6.4) that there were differences between the models, the spatial presentation of the results shows that the locations of change are quite clearly different across the models (for example, compare change in the extreme the north-west of MCSW across Figures 6.2 (a)-6.2 (c). The greater extent of change in the AMB is also apparent.

The visual comparison can be extended by considering how consistent the simulated land uses were across models (i.e. overlaying the simulated land uses from the individual models and looking for areas of agreement).

Figure 6.3 shows the number of times a particular cell was in the same simulated land use category across the models. The darkest shading indicates the areas of greatest agreement (i.e. black = land use the same in all three models) and this covered 61.7% of MCSW. In contrast, only 2.1% of the study area had a simulted land use that was different across all three models (light shading).

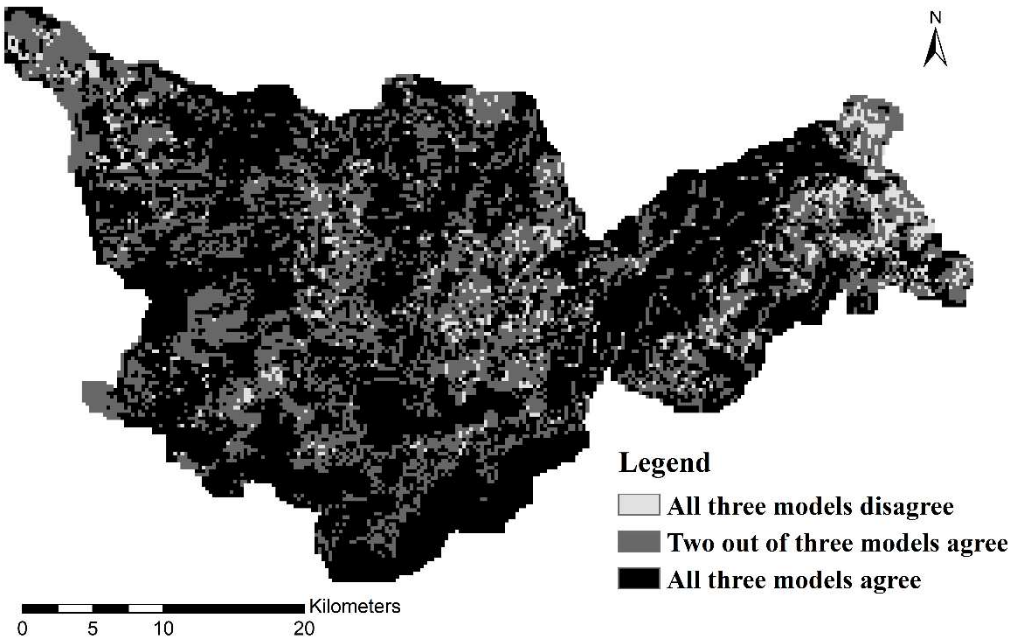


Figure 6.3 Land use agreement from 2025 model simulation for MCSW (darkest shading indicates greatest agreement across models)

Within Figure 6.3, the simulation areas where all three models agree (the darkest colour), typically relate to unchanged cells in the Forest and Rice categories (Table 6.1). The different processes in the models may helps to explain areas where only two models agreed, or where all the models were different. For example, in CA-Markov a cell changes its land use based on past trends and those of neighbouring cells. In contrast, while ABM also applies a neighbourhood effect, it also takes into account farmer behaviour and environmental characterestics. This leads to divergences between the models.

The models did however share some common inputs, for example the ABM included suitability mapping from the MCE, which may partially explain the (large) areas of agreement between the models.

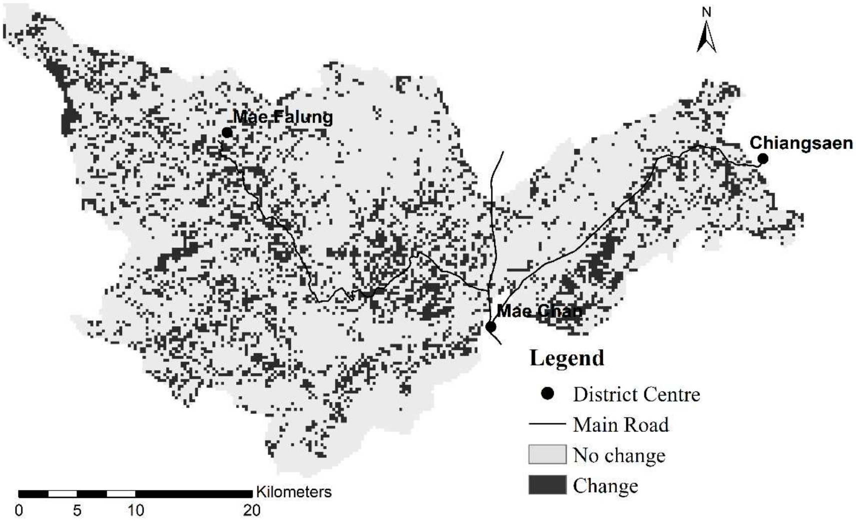
Following the evaluation of the spatial distribution of the outputs it is helpful to consider how plausible the simulated trends are by evaluation against observed data. This is addressed in the following section.

6.2.2.2 Evaluation against observed data for 2018/19

Simulations for 2025 were evaluated in the previous sections (6.2.1 and 6.2.2.1) against observations from 2016, but outputs can also be compared with observed data for 2018/19.

Observed land use change in MCSW from 2016 to 2018/19 is presented in Figure 6.4 (a). Comparing the simulated changes from all models (2016 to 2025, Figure 6.2), the pattern of land use change from the ABM simulation (Figure 6.2(c)) is most similar to the observed 2018/19 changes map, though the ABM model does not predict any change in the north-west of the study area (Figure 6.4). Figure 6.4 (b) shows the number of times a cell changed in the simulations. Through a visual inspection, these areas of simulated change broadly corresponded with the observed pattern of change (Figure 6.4 (a)). Thus, the implication is that modelling is able to identify the overall pattern of change quite well.

(a) Observed changes from 2016 to 2018/19



(b) The number of times out of three that an individual cell changed in the simulations

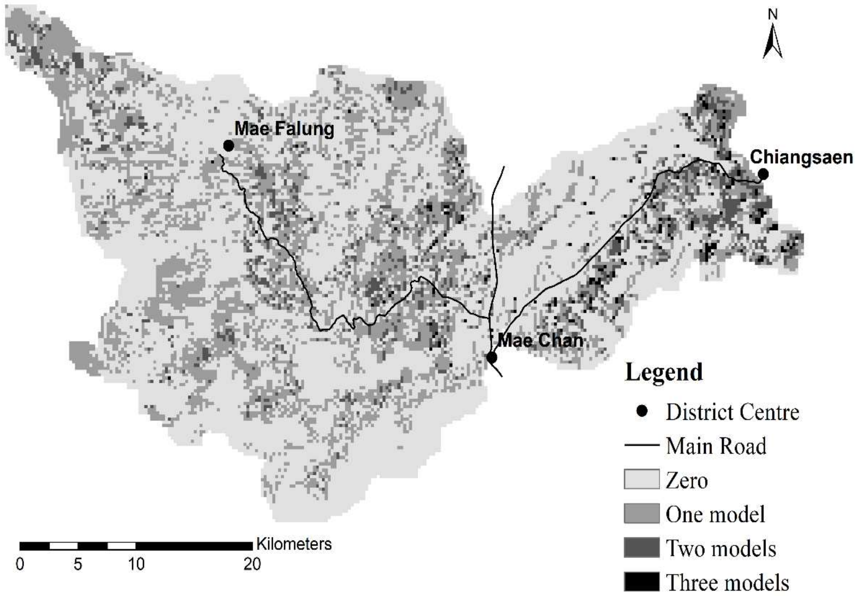


Figure 6.4 The map of (a) observed changes in land use from 2016 to 2018/19 and (b) the number of models that simulated change in individual cells from 2016 to 2025

The results in Table 6.5 show agricultural land use in MCSW 2012 (the initial validation), 2016 (the initial simulation), and 2018/19 (the observed data) and the simulated land use for 2025 in MCSW.

Table 6.5 The percentage of land use in each category in Mae Chan Sub-watershed (MCSW) in 2012, 2016 and 2018/19 (the observed data) and the simulation data from each model (2025)

Land use	Observed area (%)			Simulated Area 2025 (%)		
	2012	2016	2018/19	CA-Markov	LCM	ABM
Rice	14.82	15.73	14.54	15.54	15.56	14.65
Maize	16.89	18.01	15.03	16.57	16.70	12.88
Pineapple	1.86	2.26	3.40	2.81	2.77	5.38
Coffee and Tea	3.65	3.76	4.16	3.71	3.70	7.18
Rubber	2.70	3.91	4.45	6.25	6.10	3.83
Other Agricultural	7.86	6.81	4.94	6.14	5.86	4.71
Total Agricultural land	**47.76**	**50.48**	**46.51**	**51.03**	**50.69**	**48.64**

Change in the total amount of agricultural land use can be seen by taking the bottom row of Table 6.5 and reading across the columns. Individual rows show trends of change in each agricultural category, which can be used to help understand the direction and rate of land use change. Looking at the observed data, it can be seen that the amounts of Rice and Maize fluctuate between 2012 to 2018/19, while there is a long-term increase in both Pineapple and Rubber, and a long-term decrease in Other Agricultural. There is a small expansion in the area of Coffee and Tea over this period.

When considering the overall amount of agricultural land, ABM is the only model to show a decline in the amount of agricultural land which was also seen in the observed data. Nevertheless, simulations using CA-Markov and LCM mostly show the same trend as the observed data. The ABM shows broadly the same trend as the observed data for most crops (with the exception of Rubber), but the observed data shows a different rate of change in many cases (e.g. a faster rate of decline in Rice, and a slower rate of increase in Coffee and Tea). In the other words, ABM is better in aggregate (showing a decline in the overall amount of agricultural land) but not on an individual crop basis.

The trend in each land use category is presented in Figure 6.5. The x-axis shows the years of the observed data (2012, 2016 and 2018/19) and the simulation year (2025) while the y-axis shows the amount of land in each agricultural land use category. These graphs show the simulated land use trend from 2016 to 2025 (dashed line between years) and the observed changes from 2016 to 2018/19 (solid line between years).

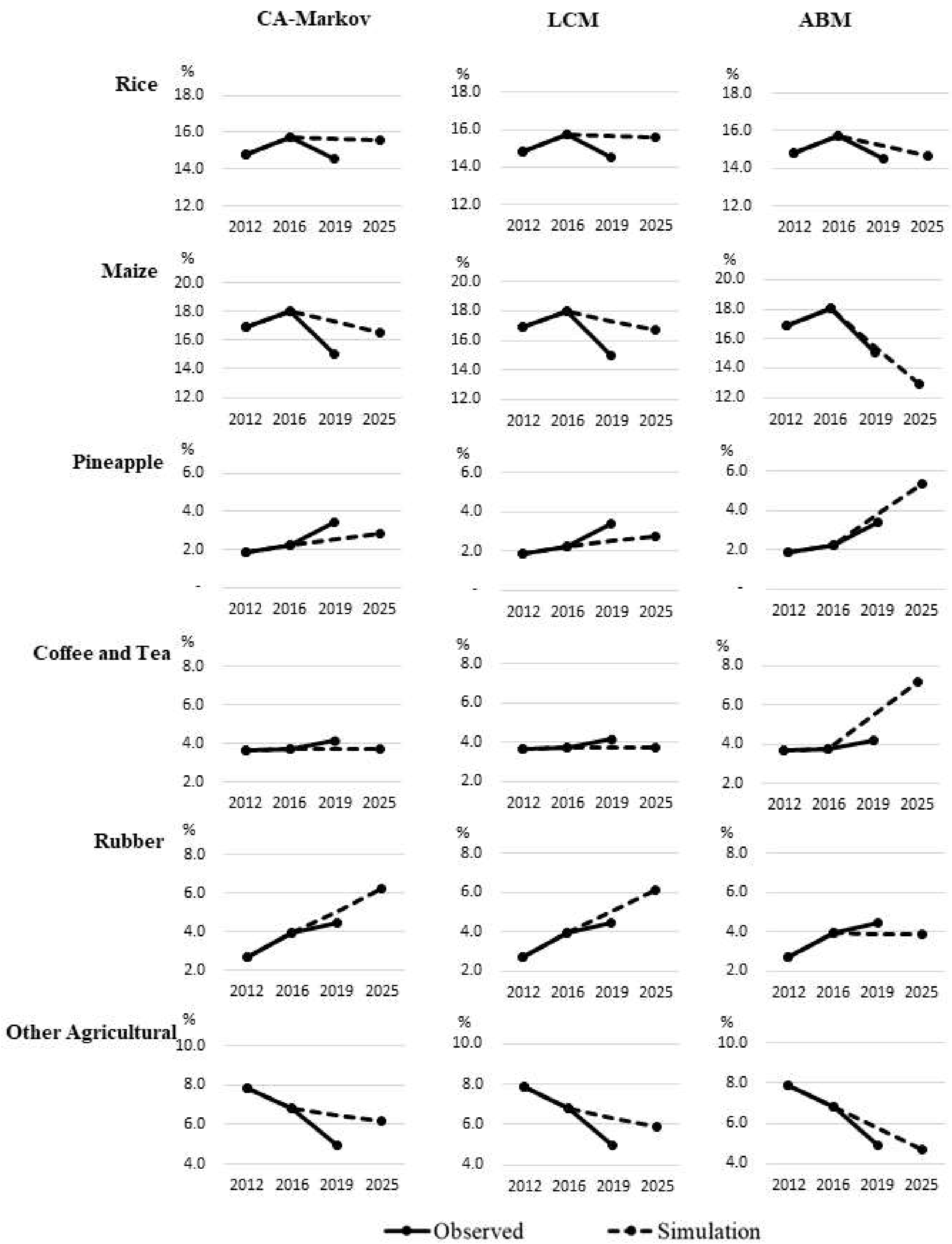


Figure 6.5 Agricultural land use changing trend in percent from 2012 to 2018/19 compared to the trend of simulation to 2025 in the Mae Chan Sub-watershed (MCSW)

The CA-Markov and LCM results are broadly similar in terms of the direction and amount of change in each agricultural land use category (Figure 6.5). The ABM on the other hand shows some differences from the other models particularly in categories such as Pineapple, Coffee and Tea and Rubber.

All models show a reduction in the area of Rice, Maize and Other Agricultural between the initial year (2016) and the simulation year (2025), but the simulation lines are often less steep than the observed line (except in the case of ABM, where the rate is broadly similar). In other words, the simulations from CA-Markov and LCM do not accurately reflect the rate of change.

For Pineapple the observed data shows a relatively large increase in the amount of this crop. All the models suggest an upward trend in the amount of Pineapple (Figure 6.5). ABM simulates the closest trajectory to the observed data line, whereas CA-Markov and LCM suggest much smaller increases over the same time period.

The observed data shows a relatively large decrease in the area of Rice (from 15.7% to 14.54% (Table 6.5)) whereas the simulations show smaller decreases or little overall change. Similarly, the observed data shows that the area of Maize has already been reduced by 2.98% relative to 2016 whereas the simulations show smaller reductions. The models also suggest decreases in the area of Other Agricultural activity and the observed data confirms that the extent of this land use has already been reduced relative to 2016.

The area of Coffee and Tea in 2019 shows a small increase from 2016 (of 0.40%) whereas the simulation outputs from CA-Markov and LCM show a small decrease in the area of Coffee and Tea. The only model to correctly simulate an increase in the expansion of Coffee and Tea is the ABM, though this model suggests larger increases (3.09%) than were actually observed (0.39%).

The observed data confirms the simulated increases in the area of Rubber from CA-Markov and LCM, but the increase in the extent of Rubber (of 0.54%) is slightly less than that which might be expected from the simulation. Validation (see Chapter 5) revealed inaccuracies across all models for the simulation of Rubber i.e. the average of producer's and user's accuracy was categorized as moderate, with less than 40% of the area being correctly simulated) and this limits confidence in the simulations.

In summary the simulation using ABM shows the greatest agreement with observed trends in land use in this study area. Following evaluation against the observed data it is helpful to consider how plausible the simulated trends are by asking local experts what they expect to happen in the future in this study area.

6.2.2.3 The experts' opinion

Four land use experts in Thailand were asked for their opinion concerning possible future trends in the economic crops in this study area. The experts were asked if they thought that the amount of each agricultural land use would increase, decrease or stay the same (see Chapter 3). The experts were also asked to give their opinion on the relevance of the different model approaches to their work and how easy the models would be to apply.

The experts were interviewed individually and are anonymized identifiers 1-4. Table 6.6 summarises the local land use experts' opinions about the likely trend in each crop over the next 10 years (2016 to 2025). The experts were shown the validation and simulation outputs and were asked to give their own opinion on each crop.

The long-term change column (Table 6.6) summarises simulated trends from the initial data (2012) to the simulation output data (2025) from CA-Markov, LCM and ABM (interpreted from Table 6.5).

Table 6.6 Comparison of the Experts' Opinion with the results of the simulations in MCSW

Land use	**Experts**				**Long-term change from models**		
	No.1	**No.2**	**No.3**	**No. 4**	**CA-Markov**	**LCM**	**ABM**
Rice	↔ / ↓	↔ / ↓	↔ / ↓	↓	↓	↓	↓
Maize	↓	↓	↓	↓	↓	↓	↓↓
Pineapple	↑	↑	↑	↑	↑	↑	↑↑
Coffee and Tea	↑	↑	↑	↑	↔ / ↓	↔ / ↓	↑↑
Rubber	↓	↓	↔ / ↓	↓	↑↑	↑↑	↔ / ↓

Trend of changes: ↔ = stable, ↑ = increase, ↓ = decrease, ↑↑ = increase larger than the average from all models, ↓↓ = decrease larger than the average from all models

For most land use types, experts agree on the trend of changes, such as the anticipated increasing trend in Pineapple and Coffee and Tea and decreasing area of Maize and Rubber. In terms of Rice and Rubber there was no consensus, both will either remain stable or decline.

The majority opinion of the experts was compared with the simulated long-term changes from the models. There are two marked areas of disagreement. For Coffee and Tea, the experts' opinion is that these crops will expand but only ABM shows the same tendency. For Rubber the experts think this crop will decrease, but ABM is the only model which shows a downward trend.

Experts agree that farmers will still grow Rice on part of their land, though the area of this crop in MCSW could slightly decrease in the future. The simulations show a stable or slightly decreasing amount of Rice (Table 6.6), which corresponds with the expert's opinion. The graph of Rice in Figure 6.5 shows a small decrease in the area of Rice from 2012 to 2018/19.

Experts consider that Rice will continue to be grown because it is a staple crop in Thailand. Most of the famers will not change all the area to other crops but will still maintain some part of their land for Rice because the farmers have a good knowledge of Rice plantation and they have a traditional cultural relationship with this crop (which is unlikely to change). The reasons for changing from Rice to other crops might include reasons related to climate change. Drought, for example, is likely to reduce the yield of Rice and more drought tolerant crops may therefore be substituted.

A reason for change is to secure a higher income by cultivating higher value crops such as Pineapple or Rubber. In addition, some of the area is likely to be changed to Integrated Farming though this is only likely to affect a small percentage of the area. Integrated Farming combines many crops in the farm area with other agricultural activities (such as poultry or a fish farm) which is based on the government promotion strategy (in both study areas). Urbanisation can also cause the area of Rice to reduce. The expansion of Urban occurs near to areas which are already Urban, and the replacement of Rice occurs where Rice is located near to the existing settlement. These areas are also located in the plain area or the area of less steep slopes.

Maize is also a main economic crop. Thailand requires Maize for the animal feed industry. There has in the past been a massive upward trend in Maize cultivation and corresponding decrease in the area of Forest (to cultivate Maize). Forest areas generally occur on steep slopes and Maize can also be grown on steep ground. Between 2012 and 2016 the area of Maize increased from 16.89% to 18.01% of the study area (Table 6.5). However, between 2016 and 2019 the direction of the trend reversed with the Maize area having reduced to 15.03% by 2019. The reason for the contraction in the area of Maize is reforestation and allocation to other crops. All the experts predicted that in the next decade, Maize will continue to be grown in MCSW, but the amount will decrease (as a result of change to other higher value crops such as Pineapple and Rubber). The simulation outputs from all models show a similar declining trend that corresponds well with the expert opinion. However, the observed decline in Maize in 2018/19 is already greater than that which is simulated by any of the models. Maize has a short growing period meaning that the area of Maize is not difficult to change to other crops. This could help to explain the large changes in the area of Maize. Also, Maize is rotated with Pineapple in some parts of MCSW (Bank of Thailand, 2020).

Pineapple is grown for fresh eating and for canning. The choice by farmers to grow Pineapple depends on the market price and the demand of the food processing industry. For canning, agricultural traders buy Pineapple from the farmers' field then supply factories mainly in the eastern and the southern part of Thailand (approximately 750 kilometres and 1,000 kilometres from the study area, respectively), while for fresh eating, the farmers also sell to the traders at the field gate and sell directly to the public in the local market (or at road-side stalls). Another factor to consider is that each Pineapple plant can provide between 2-5 harvests in the lifetime of the plant with one harvest per year. It is therefore less likely to change than some of the other crops. The simulation outputs from all the models are close (showing an increasing trend) and also correlate with the opinion of the experts.

The expert opinion is that Coffee and Tea will increase, which corresponds with the outputs from the ABM simulation. CA-Markov and LCM simulate that the amount of Coffee and Tea will remain relative stable, which this corresponds quite well with the observed data from 2018/19. Coffee and Tea has an increasing trend because the customers' demand is rising as consumption changes to having coffee and tea daily. Thai coffee is a premium product, and there is also a move to produce more Coffee domestically especially from the North of Thailand (Department of Industrial Promotion, 2020). The interesting property of Coffee plantations is that they can expand in the future without any visible change in the data. This is because Coffee grows better in shade, meaning that it can be grown in association with Forest and orchards (which are classified as Other Agricultural). Where Coffee and Tea is grown it is difficult to change to other crops because these are long-life crops (10 years plus) which can be harvested many times to provide the yield over the long term. Coffee and Tea also tend to have a clustered distribution as they are often grown in large plantations. Some plantations have water storage ponds, meaning that expansion is likely to take place near to existing plantations which have these facilities.

The amount of Rubber in the study area shows an upward trend since 2012 which is an effect from the government policy to promote Rubber in the northern and northeastern parts of Thailand (Land Development Department, 2004; Rubber Authority of Thailand, 2018). It is not therefore surprising that the area of Rubber has continued to rise until 2019. Rubber is a perennial crop (with a harvesting period of over 10 years). Figure 6.2 shows a steadily increasing trend to 2025 as simulated from CA-Markov and LCM. The observed data from 2018/19 confirms this general upward trend. Despite the observed increases in Rubber to 2019 most experts argue that the Rubber area will not significantly increase but will be stable or decrease in the future, which corresponds with the outputs from the ABM simulation. The reason they believe this is because the market price has dropped due to increasing competition in the world market and the labour problem in Thailand (where it is increasingly difficult to find cheap labour). This might be reflected in the slowing rate of expansion of Rubber in this area.

The Other Agricultural area shows a downward trend since 2012. This is the effect of allocation to other crops which depends on many factors, such as the market price, irrigation failure and government policy.

Table 6.7 shows the experts' opinion of the suitability of the models for their work in MCSW. Based on the accuracy of the validation and simulation outputs and factoring in ease of application (see Chapters 5), the experts were asked to rate the potential for implementation of the different land use models within their work.

Table 6.7 The experts' opinion of the suitability of the models for their work in MCSW

Models	Experts' opinion of the models				
	No.1	No.2	No.3	No.4	Average
CA-Markov	6	4	5	4	5
LCM	8	7	7	7	7
ABM	8	7	7	7	7

The scoring: 1= very unsuitable and 9 = very suitable

All experts tended to rank LCM and ABM highly and very similarly (all score between 7-8), while CA-Markov was given the lowest score (Table 6.7). Nevertheless, all scores were in the mid-to-high range 4-8.

The experts made their evaluations using the simulation maps from all models (Figure 6.1) and, despite the difference in simulated land use from these models, it was their opinion that LCM and ABM simulations both represented possible outcomes in 2025.

6.2.2.4 Summary

The credibility of the simulations was assessed in three different ways: evaluation of the spatial distribution of the output, comparison with the observed data for 2018/19, and comparison with the expectations of local experts.

The first point to note is that the simulations produce different amounts of overall change. CA-Markov and LCM had relatively small amounts of change (5.90% and 6.05% respectively) while the ABM simulation showed 17.60% of the study area changing use over the course of the simulation.

From a visual analysis of the simulation outputs, CA-Markov simulates a very clumped pattern of change, whilst LCM produces quite a scattered pattern of change. ABM is the intermediate between CA-Markov and LCM.

Binary maps show the areas of change/no change. This makes it immediately clear that the models are performing differently in terms of the spatial allocation of change. The binary map from ABM was found to be broadly similar to the binary map showing the location of the observed changes between 2016 (the baseline year) and 2018/19

The simulations were also evaluated against the observed data for 2018/19 to identify the general trend of change and the rate of change in each land use category. In MCSW, the simulation using ABM shows broadly a better simulation of change than CA-Markov and LCM, but not for all individual crops.

A long-term trend in Rice does not seem to be difficult to simulate because it is a main land use in the study area. Whether the Rice area increases and decreases year to year depends on the weather conditions (concerning prediction of drought and flooding) and the government policy. The amount of Maize and Pineapple are quite well simulated by all models, but the change in the Rubber area is not well simulated. The reason that Rubber is difficult to simulate is because of the government policy and the market price which affect the farmers and land users' decision making. Only ABM is able to incorporate farmers' behaviour and this could explain the stable trend in Rubber as simulated by ABM in Figure 6.5.

Comparing the experts' opinion and the simulation outputs from the different types of model it can be seen that the amount of Rice, Maize, Pineapple, and Other Agricultural in MCSW from all models are not markedly different to the expert's opinions about the tendency of these crops in the future. But looking at the simulation outputs of Coffee and Tea and Rubber, only ABM has shown a trend which are similar to the experts' opinions.

6.3 Lam Mun Sub-watershed (LMSW)

6.3.1 Simulation of agricultural land use in 2025 for Lam Mun Sub-watershed

Following validation of the model for 2015 (see Chapter 5), land use in LMSW was simulated for 2025. The outputs of the simulations are presented in Table 6.8. In terms of the total amount of land use change within this study area the models simulated that 100,362 hectares (36.24%), 35,222 hectares (12.72%) and 69,470 hectares (25.02%) from CA-Markov, LCM and ABM, respectively between 2015 and 2025.

Table 6.8 Simulated land use change between 2015 and 2025 in Lam Mun Sub-watershed (LMSW)

Land use	2015 (%)	2025 (%)			%Change 2025			Average %change
		CA-Markov	LCM	ABM	CA-Markov	LCM	ABM	
Rice	66.28	52.23	66.66	55.50	-14.06	0.38	-10.78	↓ -8.15
Rubber	4.96	14.75	10.39	4.92	9.79	5.43	-0.03	↑ 5.06
Sugarcane	3.65	9.61	1.63	9.16	5.96	-2.02	5.51	↑ 3.15
Cassava	1.48	3.14	1.80	5.57	1.66	0.32	4.09	↑ 2.02
Miscellaneous	6.63	4.62	4.77	6.31	-2.01	-1.86	-0.32	↓ -1.40
Urban	5.25	5.42	5.47	8.19	0.17	0.22	2.95	↑ 1.11
Eucalyptus	5.81	5.82	4.46	4.62	0.01	-1.34	-1.18	↓ -0.84
Forest	5.26	3.84	4.42	5.25	-1.43	-0.84	-0.01	↓ -0.76
Other Agricultural	0.69	0.58	0.39	0.48	-0.11	-0.29	-0.21	↓ -0.20
Total	**100**	**100**	**100**	**100**	**36.24**	**12.72**	**25.02**	**24.66**

These simulations suggest that there would be much more change (in terms of proportion of the total area) within this study area than MCSW. This study area has a different range of crops compared to the first watershed which reflect the contrasting environment conditions (dominantly plain topography) and the particular socio-economic development of the area. In contrast to MCSW, LMSW also has a large area of Rice (Table 6.1) which covers more than half of the area while Forest, the primary land use in MCSW, is a relatively small proportion. Rice, Rubber and Other Agricultural occur in both study areas, but some crops (Sugarcane, Cassava, and Eucalyptus) are specific to LMSW, while other crops (Tea and Coffee, and Pineapple) are not cultivated in LMSW. The Other Agricultural category combines various minor crops, which are not necessarily the same in each study area.

The model simulations indicate land use transitions in each category between the baseline year (2015) and the simulation year 2025 (Table 6.8). Arranged from the category with the greatest overall change (absolute value average across models) the land uses are: Rice (decrease), Rubber (increase), Sugarcane (increase), Cassava (increase), Miscellaneous (decrease), Urban (increase), Eucalyptus (decrease), Forest (decrease), and Other Agricultural (decrease).

The simulation outputs from all models show disagreement in the magnitude of changes and sources of change, but there is some consistency in terms of direction of change. All the models agree that Cassava and Urban will increase, and that Forest, Miscellaneous and Other Agricultural will decrease.

The area of Rice is stable for one model (LCM) and falls dramatically in the other models. The area of Rubber is also stable in one model (ABM) but expands dramatically in the other two models. Similarly, the area of Forest is stable in one model (ABM) and falls in the other two models. There is no agreement between the models on Sugarcane, i.e. LCM shows a decrease while CA-Markov and LCM show an increase. LCM and ABM have a decreasing trend for Eucalyptus, while CA-Markov shows a stable amount of this crop.

The cross-tabulations in Tables 6.9-6.11 compare the simulation outputs and the baseline map. Looking at the overall results from the different simulations, it is quite noticeable that the change in CA-Markov is concentrated in certain categories (principally Rice, Sugarcane, Cassava, and Rubber). Changes in the ABM simulation are much more extensive than those for CA-Markov while LCM also shows changes between most categories (Table 6.10).

Table 6.9 Cross-tabulation comparing the area (in percent) of land use in 2015 (column) to the simulation for 2025(row) for CA-Markov in LMSW

Land use		Land use 2015									Total 2015
		FOR	URB	MIS	RIC	SUG	CAS	RUB	EUC	OTH	
Simulation 2025	FOR	3.84	-	-	-	-	-	-	-	-	3.84
	URB	0.09	5.25	0.04	0.01	-	-	-	-	0.03	5.42
	MIS	-	-	4.58	<0.001	-	-	-	-	0.04	4.62
	RIC	0.14	-	0.12	51.97	-	-	-	-	-	52.23
	SUG	0.12	-	0.01	7.57	1.87	<0.001	<0.001	-	0.02	9.61
	CAS	0.32	-	0.11	0.92	0.23	0.84	0.03	0.58	0.11	3.14
	RUB	0.53	-	0.34	5.07	1.53	0.63	4.93	1.64	0.07	14.75
	EUC	0.18	-	1.42	0.60	0.02	-	-	3.58	0.02	5.82
	OTH	0.04	-	<0.001	0.14	-	-	-	<0.001	0.39	0.58
Total 2015		5.26	5.25	6.63	66.28	3.65	1.48	4.96	5.81	0.69	100

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, SUG= Sugarcane, CAS=Cassava, RUB=Rubber, EUC=Eucalyptus, OTH=Other Agricultural)

Table 6.10 Cross-tabulation comparing the area (in percent) of land use in 2015 (column) to the simulation for 2025(row) for LCM in LMSW

Land use		Land use 2015									Total 2015
		FOR	URB	MIS	RIC	SUG	CAS	RUB	EUC	OTH	
Simulation 2025	FOR	4.32	-	0.03	0.02	-	-	-	0.04	0.01	4.42
	URB	0.04	5.25	0.03	0.12	0.01	-	-	0.01	0.01	5.47
	MIS	0.03	-	4.02	0.25	0.02	-	-	0.33	0.13	4.77
	RIC	0.11	-	1.04	65.17	0.13	0.04	-	0.16	0.03	66.66
	SUG	0.06	-	0.06	-	1.20	0.08	0.06	0.12	0.04	1.63
	CAS	0.15	-	0.14	0.07	0.29	0.50	0.04	0.52	0.08	1.80
	RUB	0.33	-	0.30	0.43	1.82	0.82	4.82	1.75	0.12	10.39
	EUC	0.20	-	1.00	0.14	0.16	0.04	0.01	2.82	0.09	4.46
	OTH	0.02	-	0.02	0.08	0.01	0.01	0.02	0.06	0.17	0.39
Total 2015		5.26	5.25	6.63	66.28	3.65	1.48	4.96	5.81	0.69	100

Table 6.11 Cross-tabulation comparing the area (in percent) of land use in 2015 (column) to the simulation for 2025(row) for ABM in LMSW

Land use		Land use 2015									Total 2015
		FOR	URB	MIS	RIC	SUG	CAS	RUB	EUC	OTH	
Simulation 2025	FOR	3.94	-	0.14	0.77	0.05	0.08	0.06	0.17	0.04	5.25
	URB	0.13	5.25	0.29	2.15	0.12	0.05	0.02	0.12	0.06	8.19
	MIS	0.08	-	3.49	1.71	0.05	0.06	0.06	0.79	0.06	6.31
	RIC	0.73	-	1.61	51.71	0.20	0.11	0.33	0.64	0.17	55.50
	SUG	0.03	-	0.11	7.59	1.17	0.07	0.12	0.03	0.03	9.16
	CAS	0.30	-	0.13	1.14	1.89	1.01	0.31	0.76	0.03	5.57
	RUB	0.03	-	0.07	0.49	0.14	0.08	3.98	0.13	0.02	4.92
	EUC	<0.001	-	0.74	0.63	0.03	0.01	0.06	3.13	0.01	4.62
	OTH	0.01	-	0.05	0.10	<0.001	0.01	0.01	0.03	0.25	0.48
Total 2015		5.26	5.25	6.63	66.28	3.65	1.48	4.96	5.81	0.69	100

Land use perspective

The majority of the study is used for cultivating Rice. According to the simulation outputs, the area of Rice would substantially reduce by 14.06% and 10.78% in the CA-Markov and ABM simulations, respectively (Table 6.8). Within the CA-Markov simulation, Rice is mostly replaced by Sugarcane and Rubber (Table 6.9), while ABM shows Rice being allocated to Sugarcane and Urban (Table 6.11). In contrast, LCM suggests that there will be a small expansion in the Rice area (of 0.38%), which would mainly occur on land currently in the Miscellaneous category (Table 6.10).

A very large increase in the area of Rubber (of 9.79%) is simulated by CA-Markov (Table 6.8). This model suggests that most of the new areas of Rubber will have been converted from Rice (Table 6.9). LCM also simulates a large increase (of 5.43%). This model suggests that most of the new areas of Rubber will have previously been Sugarcane or Eucalyptus (Table 6.11). ABM however simulates a different trend, suggesting that the area of Rubber will be almost unchanged (-0.03%) (Table 6.8).

The increase in Sugarcane areas (a result of massive change from Rice (Table 6.9 and 6.10)) is simulated to be 5.96% (using CA-Markov) and 5.51% (using ABM) (Table 6.8). In contrast, LCM simulates a decrease in Sugarcane of 2.02% as a result of allocation to Rubber (Table 6.9)

CA-Markov and LCM suggest that LMSW will see a small increase in the area of Cassava of 0.32% and 0.28% respectively (Table 6.8), the expansion of Cassava mostly occurring at the expense of Sugarcane and Rubber (Tables 6.9 and 6.10). On the other hand, the ABM simulates a large expansion of 4.09%, as a result of change from Rice and Sugarcane (Table 6.11).

The simulations from CA-Markov and LCM suggest that the area of Urban is relatively stable, while the ABM suggests that the Urban area will expand quite noticeably (Table 6.8). In this simulation Urban mainly replaces areas which were previously Forest, Miscellaneous or Rice (Table 6.9-6.11).

The area of Eucalyptus is almost unchanged (0.01%) when using CA-Markov, whereas LCM and ABM simulate significant decreases in the area of Eucalyptus of 1.34% and 1.18% respectively (Table 6.8). The LCM model suggests that existing areas of Eucalyptus will change to Cassava or Rubber (Table 6.10), though the ABM suggests that it would be replaced by Miscellaneous, Rice and Cassava (Table 6.11).

The area of Other Agricultural is expected to slightly decline by 0.11%, 0.21% and 0.29%, using CA-Markov, ABM and LCM respectively compared to 2015 (Table 6.8). The Other Agricultural category is made up of various small-amount crops (such as Mango and Pasture). The percentage of decline in the area of Other Agricultural in CA-Markov is noticeably smaller than LCM and ABM, however this is one of land uses which shows greater agreement between the models.

Model perspective

The cross-tabulation data (Tables 6.9-6.11) and the spatial presentation of the results shows that the patterns of change are quite markedly different across the models. CA-Markov shows the greatest change and LCM the least. The amount of change in this sub-watershed is appreciably larger than in MCSW (further comparison between the sub-watersheds will be presented in in Section 6.4).

A feature of the simulation using CA-Markov is an upward trend in the overall area of agricultural land (Table 6.8), with agricultural land replacing land which was previously in the Forest and Miscellaneous categories (Table 6.9). The CA-Markov simulation shows a very large decrease in Rice (of 14.06%) offset by a massive increase in the area of Rubber (from 4.96% to 14.75%) of the overall area), a large expansion in sugarcane (from 3.5% to 9.61%) and substantial increase in Cassava (from 1.48% to 3.14%).

The LCM simulation shows a similar increase in the overall area of agricultural land (Table 6.8). In this case, however, agricultural land is replacing land which was previously in the Miscellaneous category (Table 6.10). The LCM simulation show much less overall change compare with the other models. The extent of Rice for example is almost unchanged this model (66.66% in 2025 compare with 66.28% in 2015). There would also be a substantial increase in the area of Rubber (from 4.96% to 10.39% of the overall area) according to this model. This would be balanced by declines in Sugarcane, Miscellaneous, Eucalyptus and Forest.

The ABM also simulated a total increase in the area of agricultural land (Table 6.8), however in this case it would be due to a decrease in the area of Forest and Miscellaneous (Table 6.11). There would also be a massive decrease in the area of Rice of 10.78%. The simulation suggests that the area of Sugarcane and Cassava would see large increases from 3.65% to 9.61% and from 1.48% to5.75% of the total area, respectively (Table 6.8). The area of Rubber is virtually unchanged in this simulation.

This section has considered the changes in numerical terms. Other ways of assessing the plausibility of the models are considered in the following section.

6.3.2 Evaluating the model simulations for the Lam Mun Sub-watershed

The following section evaluates the outputs from the models in a number of different ways: a visual analysis of the output maps, comparison with the observed data from 2018/19 and comparison with the predictions of local land use experts. The set of outputs which were used for the evaluation in this study area are the same as for MCSW (Section 6.2.2).

6.3.2.1 Evaluation of the spatial distribution of the outputs

The simulation maps for 2025 from all models are shown in Figure 6.6. A visual comparison of the three scenario maps for land use in 2025 was undertaken.

All three of the simulations show slightly different patterns of change from the initial map (Figure 6.6 (a)). CA-Markov produces a very clumped pattern of change (Figure 6.6 (b)) while LCM and ABM simulate quite scattered changes (Figures 6.6 (c)-6.6 (d)).

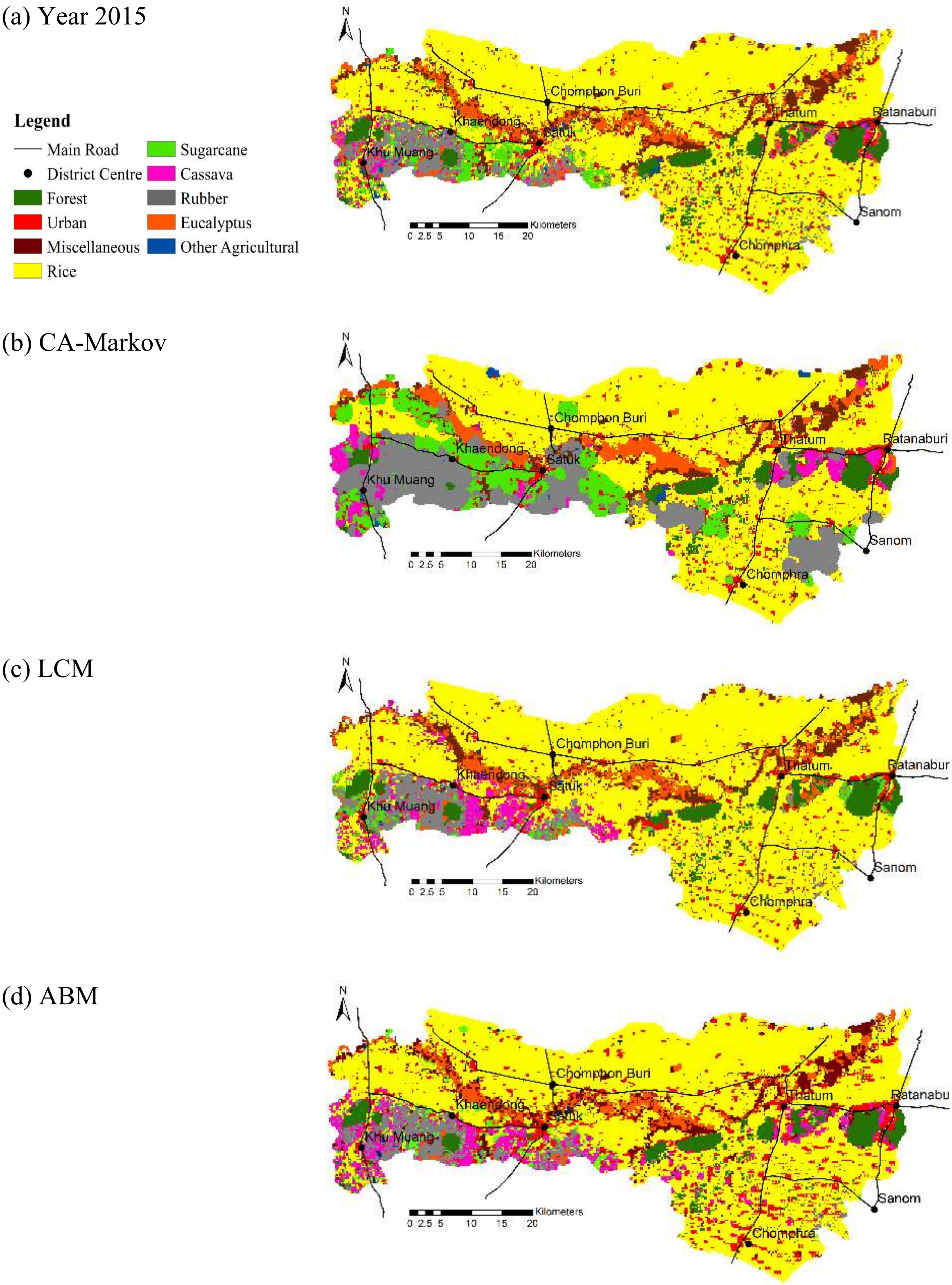


Figure 6.6 Land use in LMSW in (a) 2015 and simulated land use in 2025 using (b) CA-Markov, (c) LCM, and (d) ABM

From a visual analysis, the simulation map from CA-Markov (Figure 6.6 (b)) shows different locations of changes in the Sugarcane, Cassava, Rubber and Eucalyptus distributions when compared with LCM (Figure 6.6 (c)) and ABM (Figure 6.6 (d)).

The ABM shows less change in the western part of LMSW, but more change elsewhere when looking at the color of the land use categories. The LCM simulation map shows a mix of different land uses in the southwestern part, which is similar to ABM simulation, but the eastern part of map seems to be very close to the baseline year (2015) (i.e. there is very little change in this area).

The pattern of the distribution for each land use in the simulation from CA-Markov (Figure 6.6 (b)) shows that the new areas of a particular land use are clustered around existing areas of the same land use, whereas the LCM and ABM maps (Figures 6.6 (c)-6.6 (d)) show areas of changing land use that are more dispersed.

The simulation land use map 2025 from CA-Markov (Figure 6.6 (b)) appears to be very unlikely to be feasible as a potential land use map (similar to MCSW) because the distribution of some land uses (for instance Rubber) places them within existing Forest areas (which are protected) and Rubber also occurs in a very large cluster (the equivalent to being grown across a whole village or sub-district), which is unlikely to happen. As a consequence, the results are not plausible, as noted also for MCSW (Section 6.2.1).

The simulation map from LCM (Figure 6.6 (c)) shows different locations of changes in Sugarcane, Cassava and Rubber distributions when compared with ABM (Figure 6.6(d)). Nevertheless, the LCM and ABM simulation maps show allocation that are not clustered as in the CA-Markov simulation map (Figure 6.6 (b)) instead some of the land use categories have a widespread or scattered distribution.

Figure 6.7 shows the binary change/ no change maps highlight alternations of land use across LMSW for each model. The spatial distributions of simulated areas of change between 2015 and 2025 from CA-Markov is shown in Figure 6.7 (a), for LCM in Figure 6.7 (b) and for ABM in Figure 6.7 (c).

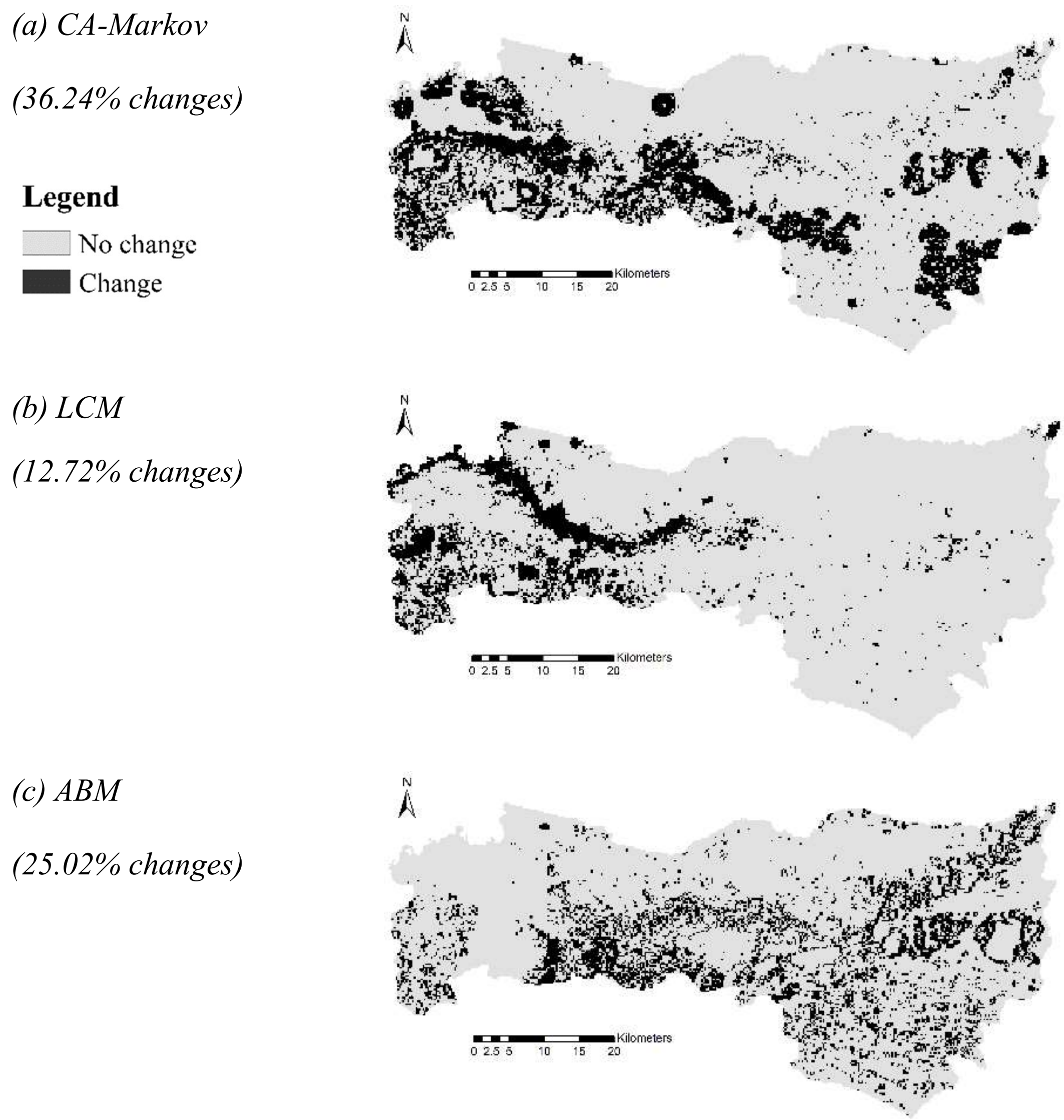


Figure 6.7 Changes in land use from 2015 to 2025 as simulated by (a) CA-Markov, (b) LCM, and (c) ABM models of LMSW

As noted earlier in the aggregated results of total land use change (Table 6.8), the simulated change area for CA-Markov is substantially larger (36.24%) than those for ABM (25.02%) and LCM (12.72%). It can be seen immediately from the maps that the distribution of change varies across the models.

Considering the binary change/no change using CA-Markov most of the changes are from Rice, Eucalyptus and Miscellaneous, whilst using LCM the majority of these areas are from Sugarcane, Eucalyptus and Miscellaneous with a lesser amount from Rice. The changing areas identified using ABM indicate that most of these areas are allocated from Rice, Sugarcane, Eucalyptus and Miscellaneous. In the baseline map (2015) the area of Rice covers a majority of the area except in the south-west (Figure 6.6 (a)). The area of Sugarcane is largely represented in the southern part of the area (Table 6.7), while the area of Eucalyptus and Miscellaneous occur mainly in a line across the middle of the area (which is related to the river).

In the LCM simulation to 2025 most of the changes are from the existing areas of Miscellaneous, Sugarcane and Eucalyptus (Table 6.10). Whilst the changing areas using ABM are mostly allocated from Miscellaneous, Rice and Sugarcane (Table 6.11), for instance, the area of change in the south-central is primary from Sugarcane to Cassava.

In the baseline map (2015) the areas of Miscellaneous and Eucalyptus are located in north-west through to the Centre (along the river, see Chapter 3) and the area of Sugarcane is located in the south-central part near the roads (Figure 6.6 (a)). For example, the area of change in the south-central near the main road is mostly change from Sugarcane to Rubber.

CA-Markov (Figure 6.7 (a)) simulates a large cluster of change in the western part of the study area, and others in the south and south-east. Cross-referencing with the land use map, Figure 6.6 (b), the greatest areas of change appear to be associated with the expansion of Sugarcane and Rubber. In LMSW, the binary map of CA-Markov features a clustering of change due to the incorporation of a neighbourhood effect (Section 2.2.2 of Chapter 2 and Section 6.2.2.1 of Chapter 6).

Simulated changes from LCM (Figure 6.7 (b)) are mostly distributed in the western part of the study area where there is a long cluster (around Khandong and Satuk districts), but there is little change in the east. When compared to CA-Markov, (Figure 6.7 (a)) there is some overlap in the western part, while in the eastern part the maps are markedly different. The largest areas of change under LCM tend to be associated with the Rubber expansion.

Comparing the outcomes between LMSW and MCSW, CA-Markov produced much more change in LMSW. The reason for this might relate to the suitability of change mapping that reflects the influence of factors such as slope, annual rainfall and crops' elasticity of change for crops. The environmental factors in MCSW are stronger, even though some areas have no data (for soil fertility and soil drainage), but the majority of this area in MCSW is Forest and with steep slopes. The strong environmental factors therefore prevent this area from changing. In LMSW the environmental constraints are much weaker and the neighbourhood effect in CA-Markov in particular produces a large amount of change over a 10-year period.

Unlike the other models, change simulated from ABM is dispersed throughout the majority of the study area, but there is little or no change in the north and north-west (Figure 6.7 (c)). The largest areas of change occurred in the south and southwest (especially, around Khandong district and Satuk district to the south of the main road, but with less change in the area around Chomphra) and appear to be associated with Cassava expansion.

Figure 6.8 shows the number of times a particular cell was in the same simulated land use category across the models in LMSW. The darkest shading indicates the areas of greatest agreement and this covered 56.9% of LMSW. In contrast, only 7.6% of the study area had a simulated land use that was different across all three models (light shading).

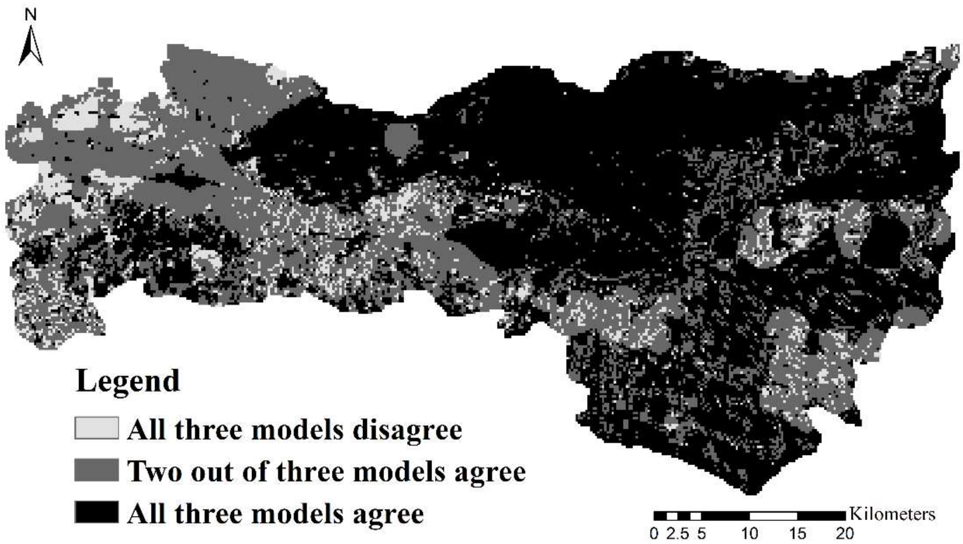


Figure 6.8 Land use agreement from 2025 model simulation for LMSM (darkest shading indicates greatest agreement across models)

Within Figure 6.8, the simulation areas where all three models agree (the darkest colour), typically relate to the large area of Rice in this sub-watershed (Table 6.8). In the floodplain paddy fields Rice may be the only suitable crop and is likely to be a stable use. Slightly higher land can support a variety of crops such as Rice, Sugarcane, Cassava, or Rubber. This could explain the large potential changes from Rice to other crops in LMSW (e.g. see Table 6.9), which are allowed by transition rules (and the elasticity of change). The historic trends (which influence the land use demand) can also help explain the change. The models did not always agree on where changes would take place, which explains the areas of disagreement. The different model mechanism also produced contrasting patterns of change, e.g. the stronger neighbourhood effect in CA-Markov compared to the ABM.

The area in the south and south west (around Khandong and Satuk districts) a large amount of change can be seen in all the simulations (Figures 6.7 and 6.8). The CA-Markov shows the majority of this area being allocated to Sugarcane and Rubber, while LCM shows the majority of this area being allocated to Rubber only. This area has a slightly higher elevation. The plain areas tend to consist of paddy fields, while the higher areas are more likely to support other crops. The environmental variables could therefore help to explain the distribution of the crops (such as Rubber).

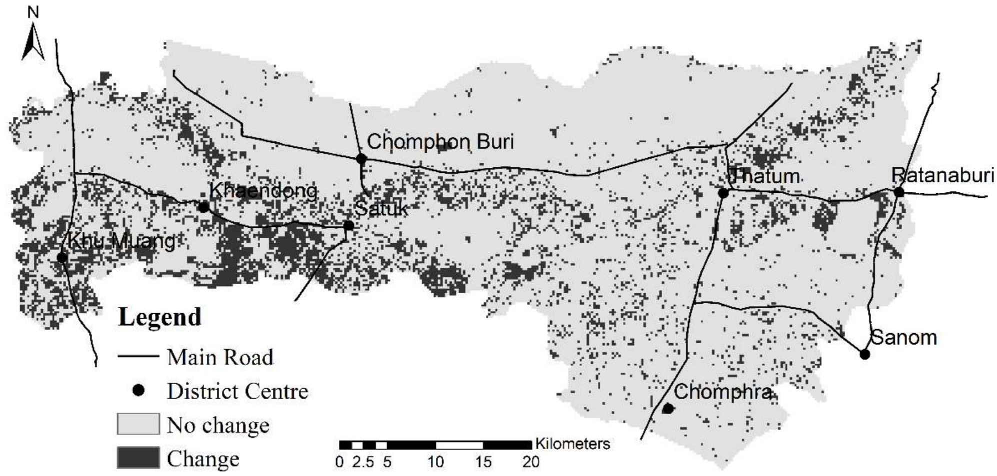
Following the evaluation of the spatial distribution of the outputs there follows a comparison between the simulations and observed data.

6.3.2.2 Comparison with the observed data for 2018/19

After comparing the observed data to the visual analysis from the spatial distribution maps, it is useful to consider how plausible the simulation trends are by assessing against the observed data for 2018/19.

Figure 6.9 (a) represents the observed land use change in LMSW from the baseline year 2015 to 2018/19, allowing comparison with simulations for 2025 (Figure 6.7). While the pattern of land use change from the ABM simulation (Figure 6.7(c)) is most similar to the observed 2018/19 changes map, the ABM model did not simulate any change in the north-west of the study area. The distribution of changes as simulated by LCM (Figure 6.7(b)) shows some similarity with the observed data with a band of change along the river (to the south of Chumphon Buri, and further change in the southwestern corner) though the LCM model does not predict any of the observed change in the eastern part. Figure 6.9 (b) shows the number of times a cell changed in the simulations. Through a visual inspection, these areas of simulated change broadly corresponded with the observed pattern of change (Figure 6.9 (a)). Many cells were unchanged in all models, representing large areas of agreement between them.

(a) Observed changes from 2016 to 2018/19



(b) The number of times out of three that an individual cell changed in the simulations

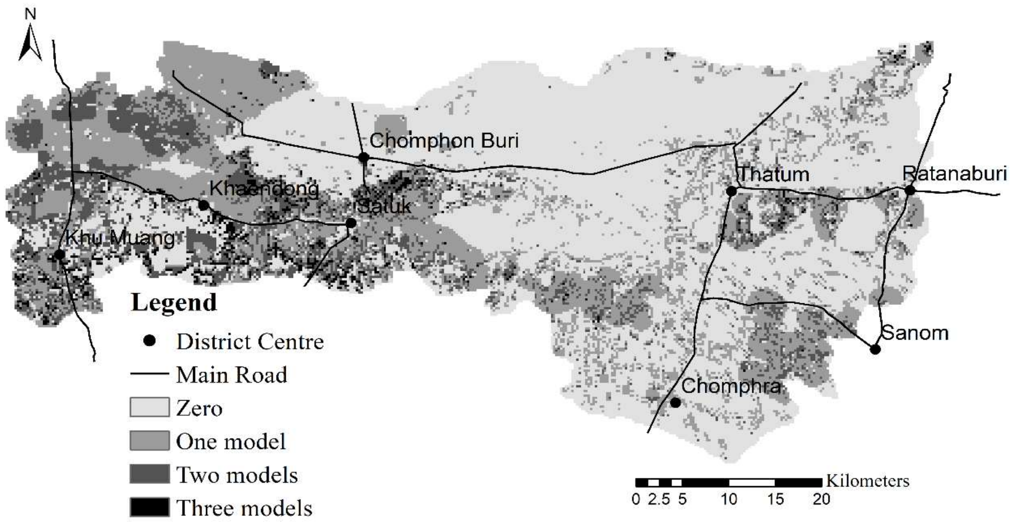


Figure 6.9 The map of (a) observed changes in land use from 2015 to 2018/19 and (b) the number of models that simulated change in individual cells from 2015 to 2025

The simulated change cells from all models (darkest shading) in Figure 6.9 (b), represents a small area, which occurred mainly within the western part of the region. These cases mostly involved changes to Sugarcane and Eucalyptus. Areas of common agreement between all three simulations are intermixed with change from two models and change from one model i.e. sometimes there is full agreement, sometimes partial and on some occasions none.

Simulation of change in just one model (Figure 6.9 (b)) occurred across the region (with less in the western part of the region). This situation occurs widely across the central and eastern parts of the region. A large part of the change in just one model was a result of the CA-Markov which showed the largest amount of change (see Table 6.8). Different amounts of change are one source of disagreement, while different spatial patterns of change also lead to disagreement between the models.

The agricultural land use categories in the historical years, (initial validation 2011 and initial simulation 2015) simulation year (2025) and the observed data (2018/19) in LMSW are presented in Table 6.12.

Table 6.12 The percentage of land use in each category in Lam Mun Sub-watershed (LMSW) in 2011, 2015 and 2018/19 (the observed data) and the simulation data from each model (2025)

Land use	Observed area (%)			Simulated area 2025 (%)		
	2011	2015	2018/19	CA-Markov	LCM	ABM
Rice	68.72	66.28	66.70	52.23	66.66	55.50
Sugarcane	2.33	3.65	2.02	9.61	1.63	9.16
Cassava	0.92	1.48	3.63	3.14	1.80	5.57
Rubber	2.44	4.96	5.05	14.75	10.39	4.92
Eucalyptus	6.40	5.81	5.20	5.82	4.46	4.62
Other Agricultural	0.99	0.69	0.37	0.58	0.39	0.48
Total Agricultural land	**81.80**	**82.86**	**82.98**	**86.12**	**85.34**	**80.25**

Change in the total amount of agricultural land use can be seen by taking the bottom row of Table 6.12 and reading across the columns. Individual rows show trends of change in each agricultural category, which can be used to help understand the trends in each land use category.

When considering the overall amount of agricultural land (Table 6.12), CA-Markov and LCM have shown an increase in the amount of agricultural land whereas ABM suggests a decline. The observed data shows a stable amount of agricultural land, which does not lend support to any of the simulations.

Looking at the developments in each crop between 2011 and 2018/19 it can be seen that the amount of Rice and Sugarcane has fluctuated, while Cassava has steadily increased. Rubber increased dramatically between 2011 and 2015, but barely increased after that. Other Agricultural and Eucalyptus steadily decreased from 2011 to 2018/19. The simulation results for each of these categories will be discussed in more detail in the following paragraphs following the same order of crops i.e. Rice, Sugarcane, Cassava, Rubber, Other Agricultural and Eucalyptus.

The simulation output from LCM is supported by the observed data for 2018/19, though this data shows that the area of Rice has already increased by 0.42%, which is more than was expected over the full 10-year period (0.38%). The CA-Markov and ABM models on the other hand simulate dramatic decreases in the area of Rice (14.06% and 10.78%), but there is no evidence for this type of change in the observed data.

The LCM simulates a decrease in Sugarcane of 2.02%, while the observed data shows that the Sugarcane area has already been reduced by 1.63% compared to 2015. The eventual results for Sugarcane could be close to or exceed the simulation, if the present trend continues. The other models simulate large increase in the area of Sugarcane, which are not realised in the observed data.

All models suggest that the amount of Cassava will have increased by 2025, but the size of the increase varies (from 0.32% to 4.09%). The observed data for Cassava confirms the expansion of this crop (by2.15%). If this trend continues, it would conform to the simulation of the ABM for this crop (an increase of 4.09% over 10 years).

The observed data supports the simulation from ABM that there will be little change from 2016 in the area of Rubber (the ABM simulates a decrease of 0.03%, while the observed data shows an increase of 0.10%). The other models suggest very large increase in the area of Rubber which have not been observed so far (and seems unlikely to occur).

For the Other Agricultural category all the models show a decreasing trend in this land use. There is not a large difference between the models. The decreasing trend in Other Agricultural is confirmed by the observed data. Other Agricultural is a relatively minor land use in this study area with less than 1% of the land being classified as Other Agricultural. The results show that some of the Other Agricultural land in this study area has transitioned to other crops.

The LCM model simulates a decrease in the area of Eucalyptus (of 1.34%). The observed data shows that the area of Eucalyptus in 2018/19 has been reduced by 0.61% so, if this trend continues, it will confirm the simulate of the LCM and ABM models quite well.

The graphs in Figure 6.10 show the change in each agricultural land use category from 2011 to 2018/19 as a solid line and then as a dashed line though to 2025. The x-axis represents time, from the initial observed year (2011) to the simulation year (2025). The y-axis shows the amount of each land use as a percentage of the total area.

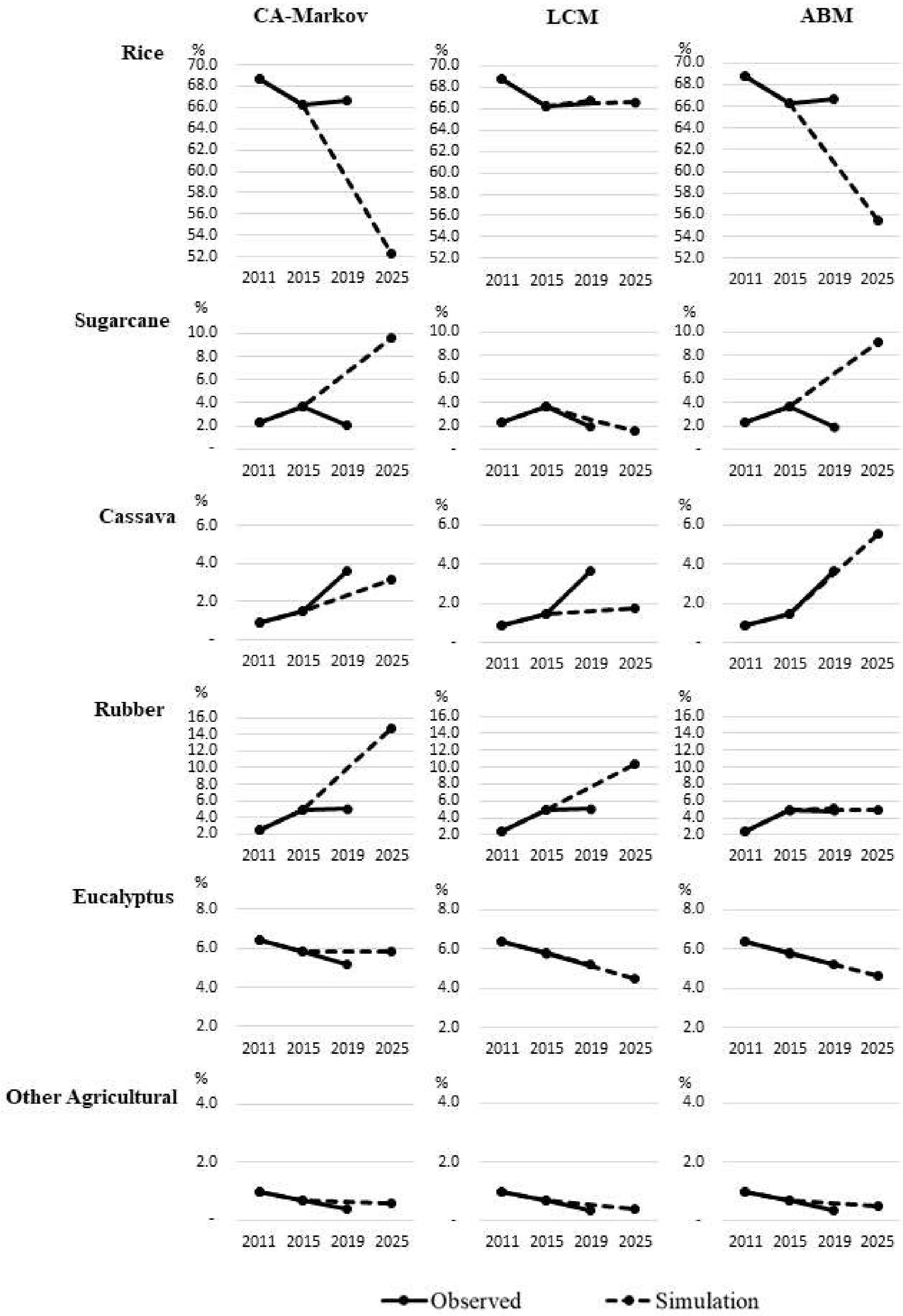


Figure 6.10 Agricultural land use changing trend in percent from 2011 to 2018/19 compared to the trend of simulation to 2025 in the Lam Mun Sub-watershed (LMSW)

The graphs present the same data in a graphical format, which makes it easy to visualize the trends. There is some agreement between the models in many land use categories. Comparing the three models the simulation LCM shows the greatest agreement with the observed data, though it does not always agree well.

Looking at the individual models in more detail it was decided to start with LCM as this was the best simulation in this study area. The LCM shows broadly the same trend as the observed data for most crops (with the exception of Cassava and Rubber). The observed and simulated trends are not always well matched however (e.g. the observed amount of Rubber is stable though the LCM suggests a massive increase, and the observed increase in Cassava is much larger than the LCM suggests). A distinct difference between the model simulations is that the LCM simulation shows a stable amount of Rice, which is reflected in the observed data. ABM is the only model to show a stable amount of Rubber, as seen in the observed data. The simulations from ABM are better in aggregate (showing a decline in the overall amount of agricultural land) but not on an individual crop basis. Conversely, the LCM shows the same trend as the observed data in most agricultural land use categories in LMSW.

Comparison with observed data can only tell us about correspondence with the historic trends. One way to validate simulations is to seek local knowledge. Seeking local knowledge is one way to incorporate information on social, economic, or policy conditions which may also determine land use.

6.3.2.3 The experts' opinion

This section compares the simulation outputs with the experts' opinions, considering whether the simulated trends for each crop are similar to what the experts would have expected based on their knowledge. Four experts were asked for their opinion on cultivation and possible future trends in the agricultural land use in LMSW. Two experts also provided their perspectives on land use within MCSW (Section 6.2.2.3).

The opinions of local land use experts about the likely trend in each crop over the next 10 years (2015 to 2025) are summarised in Table 6.13. This information was compared with the outputs of the simulation in LMSW. The long-term change from CA-Markov, LCM and ABM represents the trend in each crop from initial data (2011) to the simulation output data (2025) (taken from Table 6.12).

Table 6.13 Comparison of the Experts' Opinion with the results of the simulations in LMSW

Land use	Experts				Long-term change from models		
	No.1	No.2	No.5	No.6	CA-Markov	LCM	ABM
Rice	↔ / ↓	↓	↔ / ↓	↓	↓↓	↑	↓↓
Sugarcane	↑	↑	↑	↑	↑↑	↓	↑↑
Cassava	↑	↑	↑	↑	↑	↑	↑
Rubber	↓	↓	↓	↓	↑↑	↑↑	↔ / ↓
Eucalyptus	↓	↓	↔ / ↓	↓	↔	↓↓	↓↓

Trend of changes: ↔ = stable, ↑ = increase, ↓ = decrease, ↑↑ = increase larger than the average from all models, ↓↓ = decrease larger than the average from all models

For most land use types, the experts' agreed on the trend of change, such as an anticipated increase in Sugarcane and Cassava and decrease of Rubber. For Rice and Eucalyptus, the experts were unsure whether the crops would decline or remain stable.

Comparing the majority opinions of the experts and the long-term changes as simulated by the models, the long-term trends from ABM are the only ones to reflect the experts' opinion across all agricultural land use categories. The long-term decreases from ABM in Rice and Eucalyptus are much larger when compared to the average amount from all models, while Cassava shows a much larger increase in this model when compared to the average.

The expert opinion is that it is likely that the Rice area will continue to be relatively stable in the future for similar reasons to the MCSW region, but there will be an increasing possibility of change to other crops that have higher value (for example Sugarcane and Cassava). The reasons for transition from Rice to other crops are to do with the issues of irrigation, flooding and drought. Reference to the graph of the simulated and observed trends (Figure 6.10) shows that the area of Rice has reduced since 2011 as the experts suggest, however CA-Markov and ABM simulate large reductions in the area of Rice. Whilst some of the Rice area could change to higher value crops (such as Sugarcane) changes of this magnitude seem unlikely.

The location of Rice can be simulated relatively accurately; however, the long-term trend is more difficult to assess. Whether the Rice area increases and decreases year to year depends on the weather condition and market price, as well as government policy.

Sugarcane is expected to increase in the future because around the study area there are six sugar factories (Chapter 3). The location of the factories provides the demand for sugarcane to support sugar production. Between 2011 and 2015 there was an expansion in the area of Sugarcane of 1.32% (Table 6.12). However, between 2015 and 2019 the Sugarcane area reduced by 1.63%. The reason for fluctuation is probably to do with the market price and conversion to other crops. It is simulated that in the future, Sugarcane will continue to be grown in LMSW and it is possible that the amount of this crop might expand. The trend of Sugarcane in Figure 6.10 reveals that the Sugarcane area has increased since 2011, and that the ABM and CA-Markov models agree with the expert opinion, that the amount of Sugarcane is likely to increase in the future. This is not however reflected in the observed data from 2018/19, which shows a reduced area of Sugarcane under cultivation. For sugarcane it is possible to know the market price in advance (as this commodity is traded in the agricultural futures market), meaning that the factory can announce the demand (quota) for each year. Moreover, the change in the area of Sugarcane may be inversely related to the area of Cassava, as these crops are often rotated. This means that the amounts of Sugarcane and Cassava can fluctuate, which makes them more difficult to simulate.

The expert opinion and the simulation trend both suggest that there will be an increase in the area of Cassava. The graph of Cassava in Figure 6.10 shows the area has risen since 2011 but CA-Markov and LCM simulate a decreasing trend between 2015 and 2025, while ABM is the only model to show a continuing increase the area of Cassava. This crop is an important processed export food to the world market while in the domestic market it is in high demand for food and energy. The interesting property of Cassava is that the period of growing and harvesting (the crops' lifetime) is shorter than Sugarcane. Sugarcane plants can produce several yields, whereas Cassava is harvested once. Cassava is more flexible in terms of harvesting, and this can help to overcome labour shortages. Sugarcane on the other hand has to be harvested at specific times of year as the factories only accept the crop for processing during certain months. The simulation outputs of all the models are similar (showing a growing trend) and are also consistent with the expert opinion, especially the simulation from ABM.

All models suggest an increasing trend in Cassava, which is reflected in the observed data. However only LCM suggests that the area of Sugarcane will decrease, which was what was observed. Both Sugarcane and Cassava are switching crops in LMSW that depend on the market prices or pest problems (which can occur sometimes).

The area of Rubber in LMSW has shown an upward trend since 2012, with the area actually doubling between 2012 and 2015 (Table 6.12 and Figure 6.10), which was an effect of government policy. The policy was to promote and extend Rubber, for which the target is 160,000 hectares (or 1,000,000 rai) in the north and north-east of Thailand. In this plan the government supported the transplant of young rubber trees with subsidies (Land Development Department, 2004; Rubber Authority of Thailand, 2018). Since 2015 however the amount of Rubber has remained more or less stable. The land use experts think that the area of Rubber will continue to be stable or decrease over the next decade (for the reason which were explained in Section 6.3.1), and this view overlaps with the simulations of ABM. The observed data for 2018/19 suggests that the area of Rubber is in fact stable. Rubber is also more difficult to change as plants have a long lifespan (over 10 years) and there is a big initial investment. This supports the simulations of the ABM model, which seems to be the most credible for this crop.

The Eucalyptus area in LMSW has shown a downward trend since 2012, and the experts predict that this trend will continue. The extent of Eucalyptus area has a decreasing trend because the high demand for Eucalyptus from the paper industry in the past is now reducing. Eucalyptus is an interesting simulation output as the modelling from LCM and ABM is clearly different from CA-Markov and appears to be more accurate for this crop, based on the observed trend. The observed 2018/19 data confirms a decreasing area of Eucalyptus which also corresponded to the expert's opinion for this crop. This supports the simulations of the LCM and ABM model, which would seem to be the most credible for Eucalyptus.

The Other Agricultural area has been declining since 2011, as a result of allocation to other crops. The decision to change to other crops depends on several factors, which include availability of irrigation, potential natural disasters such as flooding or drought, and government policy, along with the current market price of the crop and potential return.

Table 6.14 shows the experts' opinion of their satisfaction with the models in LMSW. The experts were asked to score each model (on a scale of 1-9 with 1 being the least interested and 9 the most interested) according to the extent that they would be interested to work with it based on the validation and simulation outputs and the ease of application. In terms of their satisfaction with the model, the experts were more satisfied with LCM and ABM compared to CA-Markov.

Table 6.14 The experts' opinion of their satisfaction with the models in LMSW

Models	Experts' opinion of the models				
	No.1	No.2	No.5	No.6	Average
CA-Markov	6	5	4	5	5
LCM	7	6	6	6	6
ABM	8	7	7	8	8

The scoring: 1= very unsuitable and 9 = very suitable

The experts were also asked to comment on the potential implementation of the different models. The experts gave a general opinion on the models which is reported in section 6.2.2.3. Each expert has ranked ABM the highest (all scores between 7-8), while LCM was consistently slightly lower at 6-7 (Table 6.14). CA-Markov had the lowest score from the experts (range was 4-6).

In terms of the suitability of the models for their work, the experts evaluated the models using the simulation maps from all models (Figure 6.8) and, they concluded that, despite differences in simulated land use from these models, the ABM simulation best represented possible outcomes in 2025.

6.3.2.4 Summary

The credibility of the simulation outputs can be assessed by looking at the degree of agreement between the models, agreement/disagreement with the observed data and agreement/disagreement with the expert opinion. The models show some degree of agreement with the observed data and with expert opinion, however this varies between the models depending on which crop is being discussed.

The simulations from different models displayed varying amounts of overall change, ranging from around 13% to 36% across the study area (LCM simulating the least change and CA-Markov the greatest).

The pattern of the distribution for each land use in the simulation from CA-Markov shows that the new areas of a particular land use are clustered around existing areas of the same land use (simulation to MCSW), whereas the LCM and ABM maps show areas of land use change that are more dispersed. The simulation land use map 2025 from CA-Markov appears to be very unlikely to be feasible as a potential land use map because the distribution of some land uses (for instance Rubber) places them within existing protected Forest areas and Rubber also occurs across a very large area, which is unlikely to happen.

The simulation outputs can be compared with the observed data in order to identify the general trend of change. In LMSW, the simulation using LCM tends to show the same trend with the observed data, while CA-Markov and ABM shows less agreement. However, when considering the amount of change using LCM and ABM, there are large differences between the models and the observed data. Rice and Sugarcane produce interesting simulation outputs as the modelling from LCM is significantly different from the other models. The stable trend in the area of Rice, as well as a decline in the area of Sugarcane, which was observed in 2018/19, correspond to the simulations of the LCM. The stable trend in Rice broadly corresponds with the expert's opinion. In addition, the simulation of Rubber using ABM simulates that the amount of this crop will be stable, which aligns with the broad expectation of the experts.

As seen from the experts' opinion of the simulation outputs and the type of model implementation, that LCM and ABM mostly agree with the expert opinion, but they disagree in some crops such as Rice, Sugarcane and Rubber. Indeed, the simulation outputs from ABM mostly agree with the experts' opinion but there are differences in some of the agricultural land categories.

Comparing all models, it can be seen that the overall amounts of change which are produced vary considerable across the models. The evaluation of the spatial distribution of the outputs further highlights how differently the models are performing in LMSW as not only are the amounts of change different, but the locations of change also vary between models.

Comparing the simulation with the observed data and with the expert opinion, LCM is mostly showing the same trend with the observed data. ABM shows the most agreement with the expert opinion. The evaluation of the spatial distribution of the outputs, ABM performs better than the other models in this regard (across both study area) while CA-Markov did not reflect the observed patterns that because showed a very clustered distribution.

While the LCM and ABM were the most promising simulations in this study area, there were some notable differences between the models in certain crops which demonstrates the sensitivity of land use change simulations to the modelling approach. The ABM simulation is considered to be the most plausible in LMSW because of the similar trend with the expert's opinion, the total agricultural area trend, and the change in the observed data to 2018/19.

6.4 Discussion of the land use change simulations across study areas

Different perspectives can aid analysis of the simulated land use results across the study areas.

6.4.1 The sub-watershed perspective

Agricultural land use in LMSW is predicted to undergo much greater change than in MCSW (Table 6.1 compared to Table 6.8). This is not particularly surprising because of physical and political barriers to change and differing environmental driving factors such as slope. MCSW is mostly hilly with some plain topography while LMSW is mostly plain. Steep slopes over 35 degrees in MCSW are reserved for Forest (Shutidamrong, 2004; Department of Land, 2015). Unchanged areas in simulations, especially Forest, can be due to the existing topography, which acts an environmental constraint, restricting change in the area of Forest in MCSW. The steep slopes are not only protected by law but are also difficult for agriculture. The slope in this area is a strong predictor for land uses such as forest. The reasons for the stability of the forest area can therefore be described in terms of environment factors or policy (or a combination of both).

The majority of the plain area in LMSW is given over to Rice cultivation, but this crop is unlikely to change to other crops. According to the interviews with the experts which formed part of the fieldwork, some areas of Rice are suitable for other field crops especially the plateau areas, which are appropriate for Cassava or perennial crops (such as Rubber and Eucalyptus).

In LMSW, there are very large changes in the simulation of individual crops. This is different from MCSW where the increases and decreases are smaller. The reason for this might be that there is a lot of rotation between rice and field crops (such as Sugarcane and Cassava) in LMSW (more detail in Section 6.4.2).

Another reason which could be given for the greater variability between the simulation is the larger change between land use categories in LMSW, which could be because this area has less environmental variability. This means that there are fewer barriers to change. It also suggests that land uses may be less correlated with environmental factors which makes them more difficult to model. Furthermore, where single crop forms a small percentage of the total area (e.g. Cassava and Other Agricultural in LMSW) it can create a serious challenge to accurately predict and simulate these crops, because there is not enough data to accurately model these crops (Hyandye et al., 2018).

A previous study was undertaken in Nang Rong district in Northeastern, Thailand (Heumann et al., 2012). This area has a similar topography to LMSW and had similar main crops, particularly Rice, Sugarcane and Cassava. This research indicated that the environmental factors (such as slope, soil fertility, and annual rainfall) were the important factors in crop likelihood. This can also be observed in this study in LMSW where field crops are more likely to be planted on slightly higher land which is less likely to flood. The Heumann et al., (2012) study also found that other issues such as market price, changing climate, and the decision making of farmers can influence land use change, but this proved to be difficult to model (even with ABM).

This study has found evidence for relationships between land use categories and driving forces (such as slope and rainfall) in each study area. Thus, the results illustrate how the variable driving forces affect the allocation of land use.

Considering the wider land system, farmers appear to take factors such as slope, soil fertility and annual rainfall into account when they decide what crops to grow. This means that there is also a human element in the decision making. Using the DPSIR framework this could be described as a response by the farmers to the environmental conditions (Section 2.1.2 of Chapter 2).

6.4.2 Crop perspective

In MCSW, the area of Rice, Maize, and Pineapple show a similar trend to the observed data and the experts' opinion (Rice and Maize decrease. Pineapple increases), while Rubber shows a different trend.

In LMSW, the area of Cassava and Eucalyptus show a similar trend to the observed data and the experts' opinion (increasing and decreasing respectively), while Rubber and Sugarcane show a different trend.

Some land uses (such as Rice, and Maize) may be inherently easier to simulate than others, leading to better overall predictions in a watershed where they are dominant.

The areas where the simulations for all three models agreed in MCSW typically occurred in the Forest and Rice categories. Those in the Rice area relate to unchanged cells. Also, in LMSW, areas where all three models agree tend to occur in the Rice category, but Rice was also the largest decreasing area in 2025 according to some simulations. The reason for this is the large proportion of Rice in this study area (over 50% of the land), with large areas unchanged in all simulations.

A decreasing trend in Rice, for example, is not difficult to simulate because Rice is an easy crop to change to other crops, which can explain the decreasing area of Rice. Where this is a continuation of the same historical trend, this transformation would be reasonable and is expected. For example, studies in which Rice covered a majority of the area have shown well-simulated results, both in Thailand (Tienwong, 2008) and in Indonesia (Utami and Ahamed, 2017; Riadi et al, 2018).

Maize occurs only in MCSW and is well predicted. Maize shows a decreasing trend because new areas of Maize are mostly allocated from Forest, then Maize converts to other crops, especially Coffee and Tea or Rubber.

Variations in accuracy between the different crops, particularly in LMSW, may be related to differences in the crop cultivation time between perennial crops (Coffee and Tea, Rubber and Eucalyptus) and field crops (Maize, Pineapple, Sugarcane and Cassava). Where the farmers' decision-making concerns changing Rice or field crops to perennial crops it is a long-term cultivation decision. Perennial crops (Coffee and Tea and Rubber) have a longer lifespan and require a greater initial investment, which also means there is a longer time to receive a return, it is therefore likely that these areas are going to be Coffee and Tea or Rubber for 15 years or longer. Conversely, field crops like Sugarcane and Cassava are rotation crops with inherently shorter average growing times (the cultivation term for Sugarcane is 1-3 years, while for Cassava the average cultivation term is about one year).

Field crops, such as these, are easier and more likely to change and are therefore difficult to predict in long-term simulations.

Rubber is difficult to predict in both study areas because recent policy change is affecting the results. In other words, the historical land use changes show an increasing trend, but during the simulation period the market price has dropped, and the policy for Rubber has changed because the Rubber yield is over the demand.

The benefit of including the expert opinion is that this is one way to capture some of the economic (and policy) factors which are likely to determine land use choices but are difficult to incorporate within traditional land use models. This can help with evaluating the results from the model simulation as it is one way of including information on social and economic changes which are outside of the model. For example, the ABM gives a more plausible simulation for certain crops such as Rubber where the distribution is influenced by the decision-making of the farmers and their willingness to change.

Previous studies found that differences in the accuracy of the prediction also existed between the individual land use categories, especially in land use categories that covered a small proportion of the area (Kexin et al., 2019). This also appears to be the case in this study.

6.4.3 The model perspective

Looking at the performance of the model simulation alongside the experts' opinion and the observed data trend, CA-Markov simulation outputs from both study areas are not reliable as the allocation areas disagree with the observed spatial patterns (2018/2019). In MCSW, the simulation using ABM is generally better than LCM and CA-Markov, because it shows a similar trend with the expert's opinion and the observed data, for many crops. On the other hand, in LMSW, the LCM and ABM were the most promising simulations. The LCM simulation corresponds better with the observed data, whereas the ABM simulation presents a similar trend to the expert opinions.

Model agreement between the study areas varies, so that, for example, in MCSW the results from LCM are somewhat similar to CA-Markov, while in LMSW they are clearly different from CA-Markov. Both models, however, are implemented in IDRISI in TerrSet and incorporate similar processes. The differences in simulations between CA-Markov and LCM in LMSW might be explained by the different ways in which these models calculate the land use transition probability and the neighbourhood effect. While the underlying processes are similar, LCM incorporates additional ‘variable factors’, such as slope and annual rainfall, to calculate the probability of transition from one land use to another. CA-Markov, on the other hand, only extrapolate trends from historical land use, combined with neighbourhood effects (see Sections 2.2.2 and 4.3). These features lead to large expansions in Sugarcane and Rubber (and corresponding decrease in Rice) in the CA-Markov model. This was an extrapolation of the historical trend from 2011-2015, but it was also exaggerated by the neighbourhood effect. The LCM on the other hand considers the variable factors which reflects the suitability of the land in LMSW for Sugarcane. This resulted in quite a different simulation.

Previous research has shown good model performance from LCM and in some cases better performance than CA-Markov. Examples of previous studies include Kexin et al., (2019) which found that LCM was more reliable than CA-Markov in a study in China.

In addition, some studies which have used only LCM (Mishra, Rai and Mohan, 2014; Roy et al., 2015; Chavanavesskul and Cirella, 2020) indicated a good accuracy for simulation and concluded that LCM can be an effective method to monitor land use transformation.

The calculation in ABM, on the other hand, is fundamentally different and is dependent on a set of focused agents, all of which interact to achieve certain goals, with randomness and parallelism inherited. Randomness is also integrated into the ABM to account for the individual and often unpredicted behaviors those agents may display, as well as to provide a more realistic demonstration (Scott and Koehler, 2014). Acosta et al. (2014) used ABM to understand the farmers’ decision-making and to simulate a future land use pattern. Their paper states that ABM is suitable where the area it relates to is small, where individual farmers are represented as parametrized agents, and where a high spatial resolution is used. From the evidence of this study, it is agreed that ABM requires very detailed information and input data to be successful.

Reflecting on the findings from MCSW and LMSW, the ABM performed reasonably well, but was able to simulate some land uses better than others. For example, in both study areas the ABM simulation is similar to the expert opinion but is opposite to the observed data. One reason for this is because of recent government policy changes that have altered the incentives to grow rubber.

From analysis of three different models across two different study areas, no single model could be said to be the best. In MCSW the simulation using ABM generally presents the best simulation of change. In LMSW, the LCM simulation presents the most similar trend with the experts' opinion, while ABM performs the most similar trend with the observed data. Overall, then, it is difficult to conclude that one model is definitely better in the simulation stage.

6.5 Evaluation of model performance

Model fitness for purpose is considered against a framework of evaluation criteria (introduced in Chapter 2), such as linkage potential, transferability, output reliability and model access and difficultly (Table 6.15).

Table 6.15 An evaluation of the selected models (CA-Markov, LCM and ABM) for simulation

Criteria	Models		
	CA-Markov module in IDRISI	**LCM module in IDRISI**	**ABM using NetLogo**
Relevancy	Model can be used to understand the trend of land use change (but some problems with spatial allocation e.g. clusters next to existing land use) (Sections 2.3.3 and 4.3). Also, model can evaluate multiple land use categories. This model can be used to extrapolate from historical trends.	Model can be used to understand the trend of land use change and the pattern of change (Sections 2.3.3 and 4.3). Also, model can evaluate multiple land use categories. This model can incorporate variable factors which influence the trend.	Model can be used to understand the trend of land use change and the pattern of change (Sections 2.3.3 and 4.4). It can evaluate multiple land use categories and incorporate decision-making from the behaviours of the farmers (the agents).
Applications and Technical	The operation of the software can be executed in a window interface and can be automated through script and programming tools.	The operation of the software can be executed in a window interface and can be automated through script and programming tools. The model has a step-by-step approach to set it up.	The software comes with an extension and some sample models on a wide range of subjects that can be adapted for individual projects. But the users need some skill in programming code syntax.
Data requirements	The model can only use input data in the form of historical maps from two periods.	The input data consists of historical maps from two periods and variable factors (such as slope, annual rainfall etc).	The input data consist of historical maps from two periods, the driving factors (such as slope, annual rainfall etc) and the farmers' crop activities collected from field survey.
Linkage potential	The simulation input and output can be manipulated analysed and processed using GIS.	The simulation input and output can be manipulated, analysed and processed in GIS	The simulation input and output can be manipulated, analysed and processed in GIS
Transferability	No requirement for modification	No requirement for modification	No requirement for modification
Output reliability	The simulation map appears to be very unlikely to be feasible as a potential land use map (less reliability) (Sections 6.2.2 and 6.3.2).	The simulation map appears to be generally plausible as a potential land use map (general reliability) (Sections 6.2.2 and 6.3.2). Mostly similar with the observed trends.	The simulation map appears to be generally plausible as a potential land use map (general reliability). (Sections 6.2.2 and 6.3.2).
Model access and difficulty	Easiest	Moderate (between CA-Markov and ABM)	Most difficult

Beginning with the relevancy of the models, ABM is the only model which can be used to present the future behaviour of the farmers (the agents) based on past observations from the agents. CA-Markov, LCM and ABM can evaluate multiple land use categories, while some models are limited in the number of land use types (for example, Dyna-CLUE as discussed in Chapter 2).

For this study it was also necessary that models could produce outputs which were in the same format so that they could be compared.

In terms of the application and technique of the models, CA-Markov and LCM are different modules of the same software (IDRISI TerrSet) and therefore their application is fairly similar (albeit with different inputs, see below). This software is not difficult to understand, and it is also relatively simple to prepare the input data using IDRISI TerrSet or a desktop GIS such as ESRI's ArcGIS. The operation in IDRISI can be executed in a window interface and can be automated through script and programming tools. The ABM uses NetLogo and consequently has access to many samples in the model library of NetLogo (a large collection or group of pre-written simulations) while the output table can be directly exported in a number of specific formats.

In terms of data requirements (including spatial and temporal resolution), the CA-Markov requires only two land use maps while LCM also requires the variable factors (such as slope, rainfall, soil fertility etc.). The IDRISI software which is used for CA-Markov and LCM requires input data in the form of a raster map (see Section 4.3). The ABM uses additional data from the farmers' survey information. The ABM input data is flexible and can also convert input data from other software formats (for example, ASCII format).

Regarding linkage potential and the transferability of the model, all models are similar in the ability of the model tools or software function to join with other software; for example, the results of simulation maps can be easily displayed in GIS software.

Summarising the output reliability, CA-Markov shows less reliability while LCM and ABM show general reliability (see previous discussion in Sections 6.2.2, 6.3.2 and 6.4). Output reliability also varied between land uses. The simulation maps from ABM and LCM appear to be generally plausible as a potential land use map, while CA-Markov show less reliability. While LCM is 'mostly similar' with the observed trends ABM is 'mostly similar' with both the observed trends and the expert's opinion.

Considering model access and difficulty, the CA-Markov is the easiest to use (requiring only two land use maps) while ABM is the most complicated to use. ABM requires an understanding of how to design and implement (NetLogo) programming language (or the code for the model). As far as the model setting up and pre-processing for this study, the CA-Markov or LCM required less than five days while ABM involved more than 14 days work.

The model selection criteria for supporting the land use modellers and planners consists of relevancy, applications and technical, data requirements, linkage potential, transferability, output reliability, model access and difficultly. Some criteria were considered in the early part of the study (during the literature review of the models). Results herein have shown that a decision to confirm the most appropriate model for a particular study cannot be made before the validation and simulation process. Planners, however, may not always have time to validate separate models and here some recommendations can be made.

This study performed multiple simulations using different models (CA-Markov, LCM and ABM) (see Chapters 4-5) to compare performance. This study selected these three models for the simulation stage as they proved to be the best models from the initial validation work. The model selection agreed with findings from previous studies which have also applied these models in different contexts. This study however compared between three different models and it also included a thorough model evaluation which makes it one of the most comprehensive studies. Since interim data (for 2018/19) and expert opinions were obtained it was also possible to evaluate models at both the validation and simulation stages. This highlighted contrasts in performance with CA-Markov doing noticeably better in validation than simulation. The reverse was true for the ABM. These differences can be related to model characteristic (e.g. the ability to incorporate farmer attitudes in the ABM) and highlight that the nature of the model may be at least as important as validation performance when selecting a model for simulation purposes.

The findings of this study suggest that ABM or LCM could be appropriate models to monitor and simulate land use change in Thailand. This work is essential to improving land use allocation in the and formulating feasible land use planning policy in the country. Where the land use planners' interest is to understand the decision-making and behaviors of farmers and their influence on land use change, ABM is a particularly suitable model to select.

6.6 Conclusion

This chapter synthesized findings from two study areas to simulate land use change from three different models and evaluate their credibility. Evidence was used to assess, the extent to which the simulations from the different models agree or disagree, how simulations compare with observed data and how simulations compare with the understanding(s) of local experts.

This section also answered the following research questions; what are the simulations from the different models, to what extent do the simulations from the different models agree or disagree? How do simulations compare with observed data? How do simulations compare with the understanding(s) of local experts? what is the model selection? and what is the land use simulation for 2025 in the study areas?

What are the simulations from the different models? To what extent do the simulations from the different models agree or disagree?

In terms of the total amount of land use change from an initial year to 2025, the magnitude of simulated changes was different in each study area, as might be partly expected from the different in their size, biophysical characteristics (e.g. topography and climate) and consequent use of land. The plain topography of LMSW, for example, presents fewer environmental constraints, and this could explain the greater magnitude of change.

From the visual analysis of simulations, the map from CA-Markov shows land use changes which are geographically clustered, while those from LCM and ABM show more dispersed distributions of changes, though ABM has shown more change.

At the crop level, some land use categories show little consensus between models; for example, the simulation of Rubber, Coffee and Tea and Sugarcane outputs in 2025 from CA-Markov, LCM and ABM show different trends. The period of cultivation for each crop influences the likelihood of change and the decision-making process. Rice and field crops (such as Maize, Sugarcane and Cassava) are easy to change to other crop in one year or a few years and this can affect the reliability of the results.

In some places, the area of Rice is very stable and does not change at all, and is therefore relatively easy to simulate. However, there are other places where Rice is grown in rotation with Sugarcane or Cassava and in those circumstances, it is much harder to simulate.

The discrepancies between the results reflect how the models are designed and how they operate. CA-Markov, LCM and ABM use different techniques to calculate the probability of change between different pairs of land uses. CA-Markov estimates change from the suitability map that is calculated from the historical maps (without the influences of variable factors). The LCM calculates the change from transition potential map or the probability of transition with the related calculation of driving factors in each land use category. The ABM is the only model, which is able to account for the behaviour of individual farmers and to represent their behaviour within the model, which is potentially more realistic.

A possible explanation for ABM showing greater change than CA-Markov and LCM in one study area (MCSW) and a smaller change in the other study area (LMSW) is that ABM does not extrapolate forward from past trends. Change within the ABM is determined by the probability of change and the behaviour of the farmers (and their willingness to change), which can lead to different results in a variety of circumstances.

How do simulations compare with observed data?

The output reliability is an important criterion to guide the land use planner in the selection of an appropriate model. The reliability of the simulations can be assessed in a number of different ways. The first technique is to look at the plausibility of the simulation maps (and the location of change). This is followed by an assessment of the trend of change comparing with observed data and also by comparing with the opinion of local land use experts (which is covered by the next question).

The simulations were compared with the observed data. In MCSW simulations using ABM mostly show the same trend with the observed data. In LMSW, LCM shows most agreement with trends in land use categories, while the ABM simulations show some agreement for many of the agricultural land uses, but not for major crops such as Rice or Sugarcane. Comparing the simulation outputs and the observed change/no change area, the pattern of change from the ABM simulation in both the study areas are most similar to the observed changes map.

In MCSW, the trends from ABM for many crops are not similar to the observed data but when considering the overall amount of agricultural land ABM is the only model to show a decline in the amount of agricultural land, which was also seen in the observed data. On the other hand, in LMSW, the ABM appears to be quite accurate for Cassava, Rubber, Eucalyptus and Other Agricultural. The ABM, however, seems to be very inaccurate for crops such as Sugarcane; these crops are better simulated by LCM. Therefore, in MCSW shows the ABM the most agreement while in LMSW, the LCM shows the most agreement with the observed trends.

Most land use simulations work by extrapolating from historical trends (Verburg et al., 2019). The weakness of these simulations is that they cannot account for factors which are outside the model (such as change in government policy, climate or economic conditions) which could nonetheless influence the land use. With longer simulation periods there is more chance for the external factors to change, so the simulations become less and less certain with time. Future bio-physical or socio-economic changes would be likely to influence the decision making of the individual farmers (or agents) which adds another layer of complexity and uncertainty. These factors could help to explain differences between the simulations and the observed data.

How do simulations compare with the understanding(s) of local experts?

While CA-Markov and LCM showed some agreement with the experts' opinion, simulated outputs from ABM provide the greatest agreement (in both study areas).

The simulation outputs from LCM and ABM agree with the expectations of the experts for many crops. Looking at the simulation outputs of Coffee and Tea only, ABM has shown a tendency of change which is similar to the experts' opinion.

However, some crops such as Maize, Pineapple and Other Agricultural from all models are not markedly different from the expert's opinions about the tendency of these crops in the future. Some crops are hard to simulate accurately such as Sugarcane and Cassava. These crops are often rotated in this area, which means that the amounts of these crops can fluctuate. The simulation from ABM agreed with the expectations of the experts for many of the crops (e.g. increase in Sugarcane, stable amount of Rubber) and was more plausible than the other models in this respect.

What are the simulations for model selection?

According to the model performance evaluation, (see Table 6.15 for overview) especially the simulation output reliability, some recommendations can be made for land use change modelling for land use planning (at a regional or sub-regional scale) in Thailand. Many previous studies have demonstrated that relevant models (such as LCM or ABM) can be applied to modelling land use change. This study found that ABM and LCM are most suitable models for monitoring and simulating the land use change in Thailand. It is proposed that the environmental factors (heterogeneity) and the size of the study area can influence the output reliability (and usefulness) of the models. In addition, the ABM is a suitable model for land use planners to select for understanding the decision-making and behaviors of farmers and their influence on land use change. None of the models were able to capture all observed changes (either in quantity, trends or distribution), but LCM and ABM offered the greatest potential for simulating future land use in this study. There were notable differences in performance in the two study areas, which is why two models have been recommended.

What is the land use simulation for 2025 in the study areas?

An objective of this study was to develop land use change models for simulation of the land use change to 2025 in MCSW and LMSW. The simulations which were carried out provides an answer to the research question: 'what will land use in the study areas look like in 2025?' This study concluded that ABM and LCM have the most potential for simulating land use change in these study areas and it is the findings from these models which are referenced below.

The spatial pattern of land use in 2025 in MCSW from LCM would see a small increase in the total agricultural land (from 50.48% to 50.69% of the total area) and Forest (from 41.43% to 41.65% of the total area) compared with 2016. Urban would also increase slightly from 4.62% to 4.73%, whereas the Miscellaneous category would decrease (from 3.47% to 2.93%). In relation to the agricultural crops in MCSW, the area of Maize, Other Agricultural, and Rice would decrease, while Pineapple and Rubber would increase. The amount of Coffee and Tea would be almost unchanged.

The land use in 2025 in MCSW from ABM would see a decrease in the total agricultural land (from 50.48% to 48.64% of the total area) and Forest (from 41.43% to 41.18% of the total area) compared with 2016. On the other hand, Urban would increase from 4.62% to 6.88%. In relation to the agricultural crops in MCSW, the area of Maize, Other Agricultural, and Rice would decrease, while Coffee and Tea and Pineapple would increase. The amount of Rubber would be almost unchanged.

The simulation from ABM suggests that a small amount of deforestation could occur. According to the historical land use change in this area, existing Forest often changes to

Maize cultivation. An increasing concern is the rising demand for food, related to population growth. This can cause agricultural expansion and further loss of forest. Drivers of land use change (such as increasing food demand) are difficult to incorporate within the model, which can lower confidence in the simulation.

Considering the simulation of the land use from LCM for 2025 in LMSW there would be a decrease in the total amount of agricultural land from 82.86% to 80.25% between 2015 and 2025 and a decrease in the amount of Forest (from 5.26% to 4.42%). Urban would increase from 5.25% to 5.47% over the same period. Looking at the changes at the crop level, the area of Sugarcane, Eucalyptus, and Other Agricultural would be decreased, while Rice, Cassava and Rubber would be increased.

The simulation of the land use from ABM for 2025 in LMSW suggests, there would be a stable amount of Forest (from 5.26% to 5.25%), but a decrease in the total amount of agricultural land from 82.86% to 80.25% between 2015 and 2025. Urban would increase from 5.25% to 8.19% over the same period. Looking at the changes at the crop level, the area of Rubber would be stable, the area of Rice, Eucalyptus, and Other Agricultural would be decreased, while Sugarcane and Cassava would be increased as compared with 2025.

In LMSW, the simulation of agricultural categories (such as Rice, Sugarcane, Cassava and Rubber) is very sensitive to the techniques which are used in the simulation, which creates differences in the output. Rice could potentially change to other crops as some areas which are currently Rice may become less suitable because of climate change, while the market price can also be a problem (compounded by the strength of the currency and foreign competition). When farmers face drought or flooding problems, they cannot harvest their yield, meaning that Rice is vulnerable to these problems. Also, the government policy encourages and subsidizes farmers to change from Rice to other crops (such as Sugarcane or Cassava) that farmers can get a higher benefit and income from. This shows that a range of factors are influencing the land use system. Differences between the simulations suggest that is it difficult to model precise changes at the level of individual crops (within the agricultural land use category).

Chapter 7 | Conclusions and recommendations

This chapter provides a summary of the key research findings and recommendations for future research. The objectives of the study were to compare the ability of different land use models to predict and simulate possible land use changes at the crop specific level.

Three main sets of results have been presented which relate to: land use model validation and comparison of selected simulation models (Chapter 5), simulation of land use for 2025 and comparison of simulation outputs (Chapter 6).

7.1 Conclusions

The study assessed and compared examples of land use change from different categories of model (empirical-statistical, stochastic, and dynamic). Five models were selected for the calibration and validation: Dyna-CLUE, CA-Markov, MCE (Multi-Criteria Evaluation), LCM (Land Change Modeller) and ABM (Agent-based Model). Following validation, the CA-Markov, LCM and ABM models were selected for the simulation for 2025 because these models provided promisingly accurate and reliable results at the validation stage. This thesis addressed a number of research questions which were:

- How is land currently being used in the study areas and how has land use changed in recent years?
- Are some types of model better than others for simulating (certain types of) land use change?
- What are the possible simulated changes in land use for 2025?
- How well did the simulations perform, and which were the most robust simulations?

The two study areas both contained nine major land use categories which included various crops, as well as Forest, Urban and Miscellaneous. Some types of model performed better than others in the validation, and it was noticeable that the relative performance of the models was the same in both study areas (though the overall accuracies were higher in the second area). The simulations showed noticeable differences between the models (in terms of trend and spatial pattern), but LCM and ABM showed more agreement with the observed trends, and with the expectations of the land use experts.

How is land currently being used in the study areas and how has land use change in recent years?

The Mae Chan sub-watershed (MCSW) is situated in the north of Thailand. The mountainous western part of the study area is separated from the hilly eastern part by a wide plain. The area supports a wide range of agricultural products such as rice, maize, coffee and tea, pineapple, orange, longan, and lychee. The steepest ground is reserved for natural forest. The area of Forest has reduced from 52.33% in 2007 to 39.30% in 2016, with Forest typically being covert to Maize. The main changes over the past 10 years have been from Forest, Maize, and Other Agricultural to other crops (such as Rubber, Coffee and Tea, or Pineapple).

The Lam Mun sub-watershed (LMSW) is located in a specific problem area, with most of the area featuring sandy soils or sandy loam soils and inland soils called "Tung Kula Rong Hai". Rice covers more than 60% of the LMSW. Other land uses included Rubber and Eucalyptus plantations, Sugarcane (to supply local factories), Cassava, Urban, and Miscellaneous. The main land use changes in recent years have been fluctuations in the area of Rice, change from Rice to Sugarcane, an increase in Rubber, and expansion of the Urban area (Section 3.2)

Are some types of model better than other for simulating (certain types of) land use change?

In the validation stage the models which showed the highest (overall) accuracy were LCM and CA-Markov. The CA-Markov is a relatively simple model which relies on historic trends, while LCM is a more sophisticated model that it able to empirically assess the relationship between land use transitions and independent variables. This could explain the superior performance of LCM. The models generally performed better in LMSW than MCSW in the validation stage. This could be because of the dominance of certain types of crop (e.g. Rice), which are simulated better, leading to a higher overall accuracy. There was also a big range in accuracy between the different land use classes with some simulated well (e.g. CA-Markov), and some predicted very poorly (e.g. ABM, see Chapter 5 for more details). This was the case with all models.

The differences between study areas and between crops indicates that certain types of land use change are easier to simulate than others. None of the models were able to model small and rapidly expanding land uses convincingly. This is possibly because small land uses have less data to validate the model with. Better modelled land uses (such as Rice and Forest) tend to be strongly correlated with environmental variables which makes them easier to model. This can be seen in MCSW where there was more agreement between the simulations for 2025, possibly as a result of the stronger environmental driving forces.

Summarising the output reliability in this study, CA-Markov showed less reliability while LCM and ABM performed better. Output reliability also varied between land uses. The simulation maps from LCM and ABM appear to be generally plausible as a potential land use map, while CA-Markov appear less credible. While LCM is 'mostly similar' with the observed trends, ABM is 'mostly similar' with both the observed data trends and the opinions of experts (Section 6.5)

Since interim data (for 2018/19) and expert opinions were obtained it was also possible to evaluate model at both the validation and simulation stages. This highlighted constraints in performance with CA-Markov doing noticeably better in validation than simulation. The reverse was true for the ABM. These differences can be related to the model characteristics (e.g. the ability to incorporate farmer attitudes in the ABM) (Section 6.5).

What are the possible simulated changes in land use for 2025?

In MCSW in 2025 the simulation from the ABM model suggested that the agricultural land and the Urban area will increase, while the area of Forest will continue to decrease. Looking at the dynamics within the agricultural land use categories the area would see a decrease in the area of Rice, Maize and Other Agricultural. The largest changes would be from Maize to Pineapple and Coffee and Tea. The area of Rubber would be almost unchanged. For the simulation using LCM in MCSW, the study found that the agricultural land would decline. The area of Forest, Rice, Maize, and Other Agricultural would decrease while the area of Pineapple, Rubber and Urban would increase. Coffee and Tea would be almost unchanged while the majority of the area of Maize would transform to other crops.

Regarding the simulation for 2025 in LMSW, the simulation from the ABM model shows a small decrease in agricultural land, while the area of Forest would be stable. The Urban area would expand slightly in this simulation. The area of Rubber would be stable from 2015 to 2025. In LMSW, in 2025 the simulation suggests that Rice would continue to change to other crops such as Sugarcane and Cassava. The area of Rice could potentially change to other crops as, in vulnerable areas Rice may become less suitable due to climate change and the problem of the market price.

On the other hand, the simulation from the LCM model suggests that the agricultural land (including non-food crops) would increase. There would be changes between crops as the area of Rice, Cassava and Rubber would increase while the area of Sugarcane would decrease. The most important change would be from Sugarcane to Rubber. This shows that, whilst there were large areas of agreement between the simulations, there were also important differences.

In 2025, both study areas in this study will continue to be important contributors to food supply in local domestic and export markets. The main crops in MCSW (Rice, Maize and Pineapple) and LMSW (Rice, Sugarcane and Cassava) have the largest crop production (yield) which contributes to food security.

Considering food security across Thailand, the domestically generated supply of Rice and Other Food Crops is often larger than the per capita requirement of the local population (especially in, Rice, Pineapple, Sugarcane and Cassava). This provides continued confidence for food security and for surplus production to export which can support other regions. However, another factor to be aware of in food production is potential oversupply which will influence the market price. In this case, the farmers will face insecurity in their income (especially where they are single crop farmers).

The findings show that different models produce different results, which introduces a degree of uncertainty. In order to increase confidence in the simulations, this study has recognised and adopted several different methods of performance testing of the agricultural land use change models in simulation stage. These methods have helped to assess the performance of the simulations.

How well did the simulations perform, and which were the most robust simulations?

The performance of the models in the simulation stage was evaluated using three techniques. Firstly, binary maps (correct/incorrect cells for validation stage or change/no change for simulation comparison stage) were used to indicate implausible outputs, for example where new areas of change were predicted in the restricted forest zone. This revealed differences in the location of changes across the models, especially in the ways neighbouring cells were behaving. Secondly, the quantity and trend of change from each model was, compared with the observed data from a mid-point in the simulation period. Some differences between the models were observed in terms of trends, particularly within the LMSW, however LCM and ABM were mostly similar to the observed trends. Discrepancies between the models might be explained by the different ways in which the models calculate the land use transition probabilities and implement neighbourhood effects. Lastly the trends were compared with the expectation of local land use experts. The trends in the ABM output were most similar to the expectations of the land use experts.

The simulation results revealed differences between the study areas, and between different simulations in the same study area. LMSW showed much more change than MCSW, and there was also greater variation between the models. The likely reasons for this were physical and political (legal) barriers to change and differing environmental driving factors (e.g. slope) which tended to constrain change in MCSW, and the greater flexibility of the land uses in LMSW e.g. areas of Rice which could be quite easily switched to other crops, or areas which are under rotation and are therefore liable to change. The final selected models - LCM and ABM - were considered to be the most robust models after the comparison of the output reliability had been performed using the techniques described above.

In MCSW, the simulation using ABM provides the best simulation of change. In LMSW, the LCM simulation shows the most similar trend to the experts' opinions, while ABM shows the most similar trend to the observed data. Generally, it is difficult to conclude that one model is definitely better in the simulation stage. This emphasised the value of assessing robustness in a comprehensive way, comparing different simulations, as well as correspondence with observed data and expert opinion.

Overall, this study found that it is possible to model agricultural land use change at the crop specific level, but some crops proved difficult to model, meaning that challenges remain.

7.2 Contribution of the research

This study originated from concerns regarding the trend for agricultural land use in Thailand to decrease. There are a wide set of pressures on the land such as climate change, infrastructure development, population growth, and government policies. The changes in the extent of agricultural land is a challenge for the land use planner which means that it is useful to find a suitable model to simulate future land use.

The assessments of simulation outputs can help land use planners to select a suitable model for their work. Research was also undertaken in two study areas to understand how models perform in different geographical contexts, and how consistent the trends in land use change are across the country. This also provided evidence of the sensitivity of the models to different conditions. The research contribution of this thesis is therefore primarily to provide evidence on the effectiveness of various land use change models for simulating land use change (in the context of Thailand).

The study provides evidence that:

- Each area has its own characteristics, which would seem to influence the pattern of land use and land use change, thus different modelling approaches may be suitable depending on the particular character (e.g. environmental factors such as slope and annual rainfall, and history of changes) of the study area. In an area with strong environmental variation (such as MCSW) a model such as CA-Markov or LCM may be effective. In areas with less environmental variation social and economic factors and the decision-making of farmers are likely to be more important. The ABM is the only model examined in this study which can take the characteristics of farmers into account.
- The nature of different crops (factors influencing where they can be grown; whether they are annual, perennial or grown in rotation with other crops, the extent to which their cultivation was influenced by market and policy factors, and the size of the area they covered) is likely to influence the extent to which they can be modelled accurately.
- There is value in comparing several models in the same study area. Different types of calculation methods (involving different transition rules), using the same historical land use data and variable factors, produced different outcomes within the same study

area. This highlighted the sensitivity of the model to the particular conditions of the study area. Including multiple models was valuable when it came to the model evaluation and the testing of the simulation outputs.

- Evaluating the reliability of simulation output by a combination of visual analysis of output maps and binary (change/ no change) maps, comparison with observed data obtained within the simulation period (if possible), and comparison with the expectations of experts in related disciplines are important methods for testing model performance. Such evaluations can make an important contribution to research on the application and performance of land use change models.

As some models (CA-Markov and LCM) extrapolate from historical trends they cannot account for factors which are outside the model, which introduces a source of uncertainty. Thus, simulation testing using the models adopted in this thesis can help increase confidence to confirm the performance of the model beyond the validation assessment.

The findings are also applicable to regions beyond Thailand. There are several ways in which this study has wider applicability. Four of these are discussed further below.

The value of comparing several different models

The study revealed differences between the outputs of different types of model particularly within the plain areas (LMSW). This showed how sensitive the outputs were to the transition rule calculations within each model. It also revealed important differences between the models which could lead to contrasting conclusions about the trend and location of change.

Comparing between simpler and more complex types of model it was interesting that for MCSW, ABM was the best model, while for LMSW there was no model which was clearly the best. It might be expected that models such as CA-Markov – which are based on environmental driving factors – would perform well in MCSW because there is more environmental variability in this area. However, this was not the case. LMSW has less environmental variability and it is likely that the farmers choices are more important in determining land use change than the underlying environmental factors. The ABM might be expected to perform better in these circumstances, but the results do not entirely reflect this. The reason could be that LMSW shows greater change overall, and it is fairly easy for some Rice cultivation to transition to Sugarcane or Cassava and vice versa. This type of change is difficult to simulate even if an ABM is used as it requires a lot of data on the farmers and their intentions.

Importance of model evaluation

One important finding of this research was that the models which performed well in validation did not necessarily produce the best simulation results. This reflects differences in model. For example, the ABM incorporates data on land suitability and farmers characteristics, while giving less emphasis to historic map trends (such trends can change following government policy or economic conditions). This is important because many researchers choose a model for simulation based on the validation results, but this may have limitations if there are uncertainties regarding future conditions. The nature of a model, particularly an ability to incorporate attitudes and intentions, may be at least as important as validation results.

Why some crops are more difficult to model accurately

The overall accuracy of the models was reasonably high, but some of the individual land use categories showed low producer's and user's accuracies. This was due to a combination of the elasticity of conversion of the land use categories (i.e. the transition rule within the model not reflecting actual changes), the difficulty of modelling crop rotations, or the small quantities of some of the land uses. Another reason is that the models tend to follow the historic trends and cannot respond when this trend changes.

Circumstances where some types of model are more appropriate

CA-Markov can be used to represent and follow the historic trend of land use change and may be valuable where the trend is expected continue. The LCM can also incorporate such trends, as well as the influence of different variable factors. The ABM can include inputs such as suitability mapping from other models but is also good for reflecting differences in the characteristics of farmers and how they can influence decision making.

The choice of model may depend on the land use planner's objective. Where the land use planners' interest is to understand the decision-making and behaviour of farmers and their influence on land use change, ABM is a suitable model to select for this study. It was interesting that for MCSW ABM was the best model, while for LMSW there was no model which was clearly the best. This suggested that ABM does not always out-perform the simpler types of model. Furthermore, an ABM is can be difficult to implement over a large area because of the amount input data (e.g. surveys) required.

7.3 Recommendations for future research

Monitoring and simulating land use changes will be essential to improve land use and to formulate feasible land use plans in Thailand.

Although this study used detailed land use information (at 250×250m cell size) and information from interviews with local farmers and land use experts it is apparent that a number of research challenges in the application of land use change models still remain. To really understand the land use change process in detail, it is necessary to work on a smaller cell size (e.g. one that is consistent with the smallest field size) to achieve more accuracy in both validation and simulation processes (Lantman et al, 2011; Sohl et al, 2012; van Vliet et al, 2016). Modellers, however, should consider the computer processing power necessary to implement high resolution models and whether this capability is available to them.

Further application of this study framework to compare multiple land use models (Losiri et al., 2016) would be beneficial as model evaluation after simulation is often not recorded in previous studies. This approach could be used to increase the confidence of land use planners in simulation results and to assess uncertainty (i.e. agreement between models). The selected land use change models have sufficient flexibility that they could be adapted for use in other locations. The combination of multiple models and different evaluation techniques provided a detailed evaluation of the outputs which could be used to assess the uncertainty of the results. The simulation output reliability testing methods which were used in this study could be used to help support decision-making regarding model selection by land use planners in other contexts.

Further work on testing or confirmation should examine the simulation results with the local farmers or land users (Walsh et al., 2013). This would involve further field work to ask the farmers if the simulations are plausible in their opinion. Further research on the farmers opinions would build up from the farm scale (i.e. individual area of ownership or management) to try and understand land use dynamics across wider landscapes. The process of interviewing farmers could also increase confidence in the accuracy of the simulation results.

Towards the end of this thesis an unexpected factor occurred, namely the Covid-19 pandemic, which caused unexpected effects on food production and markets around the world. The DPSIR (Drivers, Pressures, State, Impact, and Responses) framework is a tool that can help to explore the effects of unexpected factors and situations on land use. Despite initial fears, the production of staple crops has continued and the volume of trade in these crops has expanded. Higher value products such as coffee and tea (which are sensitive to declining household income) have however seen reductions in demand (Agricultural Market Information System, 2020), which could have an effect on MCSW for example. The simulation for 2025 from ABM shows an increasing trend in Coffee and Tea, which in reality may be inaccurate for 2025 if the market demand drops.

Changes in agricultural production and land use mean that the simulations may not be accurate (as the models cannot account for unexpected events). Furthermore, the driving factors of land use can change, such as the population growth rate and the government policy can change, and this will introduce uncertainly into simulations. Verburg et al. (2019) provided some suggestions for overcoming these problems. These included trying to model the underlying drivers and couple them to a land use model (an integrated model approach) or synthesising local studies (to account for location variation).

Future study could also examine the implications of the land use change modelling for food production and land footprints (Ruiter, 2017). By calculating the relationship between the amount of food supply and population the land footprint of the regional/local population can be identified and used to understand how a rural area is supporting consumption elsewhere. Land footprints can be an effective way to look at food security as land is a finite resource.

This thesis demonstrates that crop-specific modelling is possible, though some challenges remain. Such modelling is likely to become more important in countries (e.g. those of South-East Asia) as agricultural areas become more connected into regional and global economies and global economic conditions become more variable due to factors like climate change and pandemics. Comparing multiple model outputs is also likely to become more important as a way of evaluating uncertainties and identifying robust options for future land use planning.

Appendix 1 The questionnaires for the farmers

Questionnaires for Farmers

A. Agricultural activities

A1. How many total crop fields (area) do you have?

A2. What is the cost of labour which you use (ploughing/ sowing/ planning/ pest control/ harvesting/ post harvesting/ marketing)?

A3. What is your cropping method and how often do you perform each activity? (machine/labour)

A4. What is your irrigation method?

A5. How long have you grown (this) crop?

A6. How long you have you grown (this) crop?

A7. Why have you grown (this) crop?

A8. How many household labourers do you have?

A9. How often do you train about farming practice (by government &private sector)?

A10. How often do you join the activity of an agricultural cooperative or group?

B. Crop yields

B1. What was the yield for (this) crop? (Last 5 years to now (2012-2017))

B2. What is your objective for the crop yield (sell/seed/food)? How many percent?

B3. Do you have some activities to improve crop yield? If yes, what?

C. Land use information

Land right/tenure

C1. What is your land right/tenure?

C2. How long you did you own/rent the land?

C3. Do you own land that is used by another?

Land use areas

C4. What is your proportion of land use/agricultural activities? (Last 5 years to now)

C5. What is your objective for the land use? (Last 5 years to now)

D. The problems related to agricultural activities

D1. Do you have any cropping problem?

D2. How often does the problem occur?

D3. How to solve the problem?

Pests/ Lack of capital/ Insufficient land/ No clear land status/ Difficulties accessing quality seed/ Difficulties accessing fertilizer/ Fertilizer is too expensive/ Difficulties selling products/ Farm gate price is very low/ Lack of technology information/ Lack of water for agriculture/ No labour/ Disaster/ Land conflict with company/ Other

E. Plan for future (Perception of change)

E1. What is your next crop?

E2. Do you have plans to change to a new crop? (If yes, why?)

E3. Do you have plans to sell/give land to other? (If yes, why?)

E4. Do you have plans to buy land from another? (If yes, why?)

F. General Information

F1. Respondents' Name /Age /Gender

F2. How many people are dependent and living in the house?

F3. Are you ancestors from this village?

F4. How long have you/your family lived in this area/village?

F5. Education level of household

F6. What is your farming knowledge access? (school/TV/social media)

Appendix 2 The questionnaires for the experts

Questionnaires for Land use expert's validation

1. What do you think about the trend of the agricultural land use categories?

MCSW	**LMSW**
Rice	Rice
Maize	Sugarcane
Pineapple	Cassava
Coffee and tea	Eucalyptus
Rubber	Rubber
Other Agricultural	Other Agricultural

2. What is the likely reason for changing between crops in 2025?

MCSW	**LMSW**
- All land use categories to Rice	- All land use categories to Rice
- All land use categories to Maize	- All land use categories to Sugarcane
- All land use categories to Pineapple	- All land use categories to Cassava
- All land use categories to Coffee and tea	- All land use categories to Eucalyptus
- All land use categories to Rubber	- All land use categories to Rubber
- All land use categories to Other Agricultural	- All land use categories to Other Agricultural

3. What is the reason for no change in cropping in 2025? (Land use categories, see in No.1)

4. What are the possible limitations of the future land use simulation?

5. Which (agricultural) land use category is likely to change in the future?

6. How many score do you agree (suitable of models on your work) with the simulation in 2025?

Models	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
CA-Markov									
LCM									
ABM									

Score 1 = least suitable and 9 = most suitable

Appendix 3 Markov matrix

Appendix Table 3.1 transition probability matrix for 2007 (row)- 2012 (column) in MCSW

Markov matrix for 2007-2012		2007								
		FOR	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**
2012	**FOR**	**0.8666**	0.0006	0.0030	0.0002	0.1020	0.0005	0.0109	0.0098	0.0065
	URB	0.0009	**0.9918**	0.0000	0.0000	0.0010	0.0000	0.0063	0.0000	0.0000
	MIS	0.0022	0.0242	**0.7807**	0.0139	0.0568	0.0479	0.0000	0.0393	0.0349
	RIC	0.0000	0.0033	0.0003	**0.9609**	0.0130	0.0024	0.0000	0.0033	0.0167
	MAI	0.0023	0.0105	0.0397	0.0124	**0.6265**	0.0604	0.0633	0.0873	0.0977
	PIN	0.0000	0.0062	0.1691	0.0347	0.0019	**0.6986**	0.0000	0.0542	0.0354
	COF	0.0000	0.0266	0.0000	0.0133	0.0033	0.0000	**0.9052**	0.0070	0.0446
	RUB	0.0000	0.0000	0.0175	0.0158	0.0000	0.3234	0.0000	**0.4295**	0.2138
	OTH	0.0031	0.0064	0.0200	0.0089	0.3660	0.0078	0.1008	0.0444	**0.4428**

Appendix Table 3.2 transition probability matrix for 2006 (row)- 2011 (column) in LMSW

Markov matrix for 2006-2011		2006								
		FOR	**URB**	**MIS**	**RIC**	**SUG**	**CAS**	**RUB**	**EUC**	**OTH**
2011	**FOR**	**0.9831**	0.0012	0.0090	0.0010	0.0002	0.0014	0.0005	0.0021	0.0015
	URB	0.0000	**0.9965**	0.0000	0.0025	0.0005	0.0000	0.0000	0.0000	0.0005
	MIS	0.0006	0.0031	**0.9061**	0.0269	0.0010	0.0025	0.0014	0.0535	0.0049
	RIC	0.0000	0.0001	0.0007	**0.9902**	0.0048	0.0005	0.0016	0.0019	0.0003
	SUG	0.0008	0.0034	0.0038	0.0012	**0.6612**	0.0746	0.1898	0.0462	0.0191
	CAS	0.0000	0.0000	0.0037	0.0026	0.2468	**0.3506**	0.3197	0.0668	0.0099
	RUB	0.0000	0.0000	0.0017	0.0000	0.0214	0.0220	**0.8928**	0.0537	0.0084
	EUC	0.0003	0.0014	0.0131	0.0033	0.0145	0.0123	0.0437	**0.9069**	0.0045
	OTH	0.0019	0.1332	0.0004	0.6591	0.0029	0.0224	0.0068	0.0208	**0.1526**

Appendix Table 3.3 transition areas matrix for 2007 (row)- 2012 (column) in MCSW

Markov matrix for 2007-2012		2007								
		FOR	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**
2012	**FOR**	**8516**	6	29	2	1002	5	107	96	64
	URB	1	**970**	0	0	1	0	6	0	0
	MIS	2	20	**629**	11	46	39	0	32	28
	RIC	0	11	1	**3165**	43	8	0	11	55
	MAI	9	39	149	47	**2356**	227	238	328	367
	PIN	0	3	70	14	1	**289**	0	22	15
	COF	0	22	0	11	3	0	**733**	6	36
	RUB	0	0	11	9	0	194	0	**258**	128
	OTH	5	11	35	16	639	14	176	78	**774**

Appendix Table 3.3 transition areas matrix for 2006 (row)- 2011 (column) in LMSW

Markov matrix for 2006-2011		2006								
		FOR	**URB**	**MIS**	**RIC**	**SUG**	**CAS**	**RUB**	**EUC**	**OTH**
2011	**FOR**	**2549**	1	11	1	0	2	0	2	2
	URB	0	**2292**	0	3	0	0	0	0	0
	MIS	1	5	**3306**	46	1	4	2	92	8
	RIC	0	1	11	**31276**	75	8	25	30	4
	SUG	0	2	2	0	**887**	40	101	24	10
	CAS	0	0	1	0	52	**286**	67	14	2
	RUB	0	0	1	0	12	12	**1058**	30	4
	EUC	0	2	19	5	21	18	64	**2789**	6
	OTH	0	30	0	148	0	5	1	4	**262**

Appendix 4 Cross tabulation to assess accuracy

Appendix Table 4.1 The accuracy of the reality map and simulated map for 2016 of MCSW from LCM

		Reference map 2016										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**	**Total**	**User's ACC**
Simulation map 2016	**FOR**	39068	95	39	824	1187	41	12	0	105	41372	**0.94**
	URB	80	5079	124	342	250	12	18	12	74	5990	**0.84**
	MIS	318	6	3352	112	591	357	0	292	179	5206	**0.65**
	RIC	17	18	84	15052	227	187	88	69	256	15999	**0.94**
	MAI	8218	77	213	1206	16523	70	94	172	1687	28260	**0.58**
	PIN	596	29	218	359	813	1934	59	772	277	5057	**0.37**
	COF	1761	457	12	39	1068	0	4422	12	571	8342	**0.52**
	RUB	1300	47	129	309	1324	59	41	2366	372	5948	**0.39**
	OTH	750	6	191	1537	671	176	0	1229	5045	9603	**0.54**
Total		52108	5814	4362	19779	22654	2837	4734	4923	8566	125777	
Producer's Accuracy		**0.75**	**0.87**	**0.77**	**0.76**	**0.73**	**0.68**	**0.93**	**0.48**	**0.59**		
Overall Accuracy		**0.77**										

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, PIN= Pineapple, COF=Coffee and Tea, RBU=Rubber, OTH=Other Agricultural)

Appendix Table 4.2 The accuracy of the reality map and simulated map for 2016 of MCSW from CA-Markov

		Reference map 2016										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**	**Total**	**User's ACC**
Simulation map 2016	**FOR**	45,270	53	269	1,155	8,335	141	996	652	461	57,332	**0.96**
	URB	5	5,114	12	73	5	12	41	23	11	5,297	**0.88**
	MIS	0	142	2,614	135	262	164	0	58	84	3,458	**0.71**
	RIC	80	119	134	14,015	1,091	200	0	143	822	16,603	**0.97**
	MAI	4,662	190	963	919	9,795	1,330	2,361	3,373	4,076	27,669	**0.56**
	PIN	45	24	146	179	35	399	47	5	84	964	**0.43**
	COF	1,766	137	79	1,362	1,983	47	1,284	292	1,436	8,386	**0.53**
	RUB	273	6	90	1,901	205	545	0	315	801	4,134	**0.35**
	OTH	5	29	56	39	944	0	6	63	791	1,934	**0.61**
Total		52,108	5,814	4,362	19,779	22,653	2,837	4,735	4,923	8,566	125,777	
Producer's Accuracy		**0.76**	**0.91**	**0.85**	**0.79**	**0.70**	**0.77**	**0.93**	**0.42**	**0.68**		
Overall Accuracy		**0.63**										

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, PIN= Pineapple, COF=Coffee and Tea, RBU=Rubber, OTH=Other Agricultural)

Appendix Table 4.3 The accuracy of the reality map and simulated map for 2015 of MCSW from MCE

		Reference map 2016										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**	**Total**	**User's ACC**
Simulation map 2016	**FOR**	45,865	12	79	1,239	949	76	29	86	105	48,440	**0.95**
	URB	23	5,688	117	112	199	0	129	17	95	6,380	**0.89**
	MIS	119	18	3,152	112	864	411	0	297	220	5,193	**0.61**
	RIC	12	12	67	17,408	227	252	76	114	199	18,368	**0.95**
	MAI	4,578	18	286	353	14,056	188	52	554	2,917	23,003	**0.60**
	PIN	17	12	263	45	1,199	1,570	59	1,195	95	4,456	**0.35**
	COF	596	53	0	12	1,290	41	4,130	143	938	7,203	**0.56**
	RUB	489	0	213	62	1,699	188	29	1,487	524	4,690	**0.31**
	OTH	409	0	185	438	2,171	112	229	1,029	3,473	8,044	**0.45**
Total		52,108	5,814	4,362	19,780	22,653	2,837	4,734	4,923	8,566	125,777	
Producer's Accuracy		**0.88**	**0.98**	**0.72**	**0.88**	**0.62**	**0.55**	**0.87**	**0.30**	**0.41**		
Overall Accuracy		**0.74**										

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, PIN= Pineapple, COF=Coffee and Tea, RBU=Rubber, OTH=Other Agricultural)

Appendix Table 4.4 The accuracy of the reality map and simulated map for 2016 of MCSW from ABM

		Reference map 2016										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**	**Total**	**User's ACC**
Simulation map 2016	**FOR**	46786	0	588	1714	8374	475	1160	1126	1697	61921	**0.90**
	URB	436	5545	130	1058	277	74	79	62	300	7961	**1.00**
	MIS	136	0	1828	379	238	238	0	136	215	3168	**0.41**
	RIC	243	0	311	14513	758	419	40	436	996	17715	**0.73**
	MAI	3174	0	651	1103	9245	481	1109	1465	3078	20307	**0.41**
	PIN	136	0	181	289	402	526	34	289	215	2071	**0.19**
	COF	294	0	209	51	1098	74	1878	136	317	4057	**0.41**
	RUB	187	0	277	362	475	260	45	820	356	2784	**0.17**
	OTH	521	0	232	492	1675	192	226	402	2054	5794	**0.22**
Total		51912	5545	4408	19961	22541	2738	4572	4872	9228	125777	
Producer's Accuracy		**0.76**	**0.70**	**0.58**	**0.82**	**0.46**	**0.25**	**0.46**	**0.29**	**0.35**		
Overall Accuracy		**0.66**										

Appendix Table 4.5 The accuracy of the reality map and simulated map for 2016 of MCSW from Dyna-CLUE

		Reference map 2016										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**MAI**	**PIN**	**COF**	**RUB**	**OTH**	**Total**	**User's ACC**
Simulation map 2016	**FOR**	45270	53	269	1155	8335	141	996	652	461	57332	**0.79**
	URB	5	5114	12	73	5	12	41	23	11	5297	**0.96**
	MIS	0	142	2614	135	262	164	0	58	84	3458	**0.76**
	RIC	80	119	134	14015	1091	200	0	143	822	16603	**0.84**
	MAI	4662	190	963	919	9795	1330	2361	3373	4076	27669	**0.35**
	PIN	45	24	146	179	35	399	47	5	84	964	**0.40**
	COF	1766	137	79	1362	1983	47	1284	292	1436	8386	**0.15**
	RUB	273	6	90	1901	205	545	0	315	801	4134	**0.07**
	OTH	5	29	56	39	944	0	6	63	791	1934	**0.43**
Total		52108	5814	4362	19779	22653	2837	4735	4923	8566	125777	
Producer's Accuracy		**0.87**	**0.88**	**0.60**	**0.71**	**0.43**	**0.14**	**0.27**	**0.06**	**0.09**		
Overall Accuracy		**0.63**										

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, PIN= Pineapple, COF=Coffee and Tea, RUB=Rubber, OTH=Other Agricultural)

Appendix Table 4.6 The accuracy of the reality map and simulated map for 2015 of LMSW from LCM

		Reference map 2015										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**SUG**	**CAS**	**RUB**	**EUC**	**OTH**	**Total**	**User's ACC**
Simulation map 2015	**FOR**	14224	50	56	114	114	227	315	310	45	15454	**0.92**
	URB	13	14137	13	19	13	6	75	13	368	14659	**0.97**
	MIS	169	56	16105	1322	50	165	214	1587	36	19705	**0.82**
	RIC	31	243	958	180341	5669	637	2183	1058	1029	192150	**0.94**
	SUG	6	19	25	749	2936	606	1372	355	0	6067	**0.48**
	CAS	19	0	64	95	290	687	541	252	52	2000	**0.35**
	RUB	6	0	13	227	661	568	6623	355	36	8489	**0.78**
	EUC	81	19	1065	535	258	1167	2340	12054	169	17688	**0.68**
	OTH	31	6	70	182	114	38	63	97	162	764	**0.19**
Total		14580	14530	18370	183584	10106	4101	13727	16080	1898	276975	
Producer's Accuracy		**0.98**	**0.97**	**0.88**	**0.98**	**0.29**	**0.17**	**0.48**	**0.75**	**0.09**		
Overall Accuracy		**0.89**										

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, SUG= Sugarcane, CAS=Cassava, RUB=Rubber, EUC=Eucalyptus, OTH=Other Agricultural)

Appendix Table 4.7 The accuracy of the reality map and simulated map for 2015 of LMSW from CA-Markov

		Reference map 2015										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**SUG**	**CAS**	**RUB**	**EUC**	**OTH**	**Total**	**User's ACC**
Simulation map 2015	**FOR**	12044	44	38	114	107	208	277	284	22	13138	**0.92**
	URB	188	12641	183	0	0	6	19	6	15	13059	**0.97**
	MIS	1477	63	14680	1888	50	120	214	1413	45	19949	**0.74**
	RIC	38	1408	460	161251	712	190	830	375	404	165668	**0.97**
	SUG	0	343	50	10526	7265	568	1422	271	0	20447	**0.36**
	CAS	238	0	101	1164	208	1300	768	226	221	4225	**0.31**
	RUB	6	0	25	3479	1159	586	8442	561	45	14304	**0.59**
	EUC	338	19	2510	5072	422	990	1434	12621	161	23569	**0.53**
	OTH	250	13	322	89	182	132	321	323	984	2617	**0.34**
Total		14580	14530	18370	183584	10106	4101	13727	16080	1897	276975	
Producer's Accuracy		**0.83**	**0.87**	**0.80**	**0.88**	**0.72**	**0.32**	**0.62**	**0.78**	**0.52**		
Overall Accuracy		**0.84**										

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, SUG= Sugarcane, CAS=Cassava, RUB=Rubber, EUC=Eucalyptus, OTH=Other Agricultural)

Appendix Table 4.8 The accuracy of the reality map and simulated map for 2015 of LMSW from MCE module

		Reference map 2015										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**SUG**	**CAS**	**RUB**	**EUC**	**OTH**	**Total**	**User's ACC**
Simulation map 2015	**FOR**	12057	38	31	107	101	202	240	284	7	13066	**0.92**
	URB	213	12187	240	296	6	31	19	45	125	13163	**0.93**
	MIS	1320	31	12920	3278	82	132	201	1857	74	19896	**0.65**
	RIC	150	1688	1570	159796	560	157	843	484	441	165692	**0.96**
	SUG	69	418	164	10081	6981	561	1667	375	59	20374	**0.34**
	CAS	188	6	89	1258	316	1256	906	194	59	4272	**0.29**
	RUB	56	25	120	3593	1172	587	7995	742	81	14372	**0.56**
	EUC	325	44	2989	4908	661	1029	1585	11821	213	23576	**0.50**
	OTH	200	94	246	265	227	145	271	278	839	2564	**0.29**
Total		14580	14530	18370	183584	10106	4101	13727	16080	1898	276975	
Producer's Accuracy		**0.83**	**0.84**	**0.70**	**0.87**	**0.69**	**0.31**	**0.58**	**0.74**	**0.44**		
Overall Accuracy		**0.82**										

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, SUG= Sugarcane, CAS=Cassava, RUB=Rubber, EUC=Eucalyptus, OTH=Other Agricultural)

Appendix Table 4.9 The accuracy of the reality map and simulated map for 2015 of LMSW from ABM

		Reference map 2015										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**SUG**	**CAS**	**RUB**	**EUC**	**OTH**	**Total**	**User's ACC**
Simulation map 2015	**FOR**	13291	0	194	1302	164	267	685	315	121	16338	**0.81**
	URB	0	14223	273	2611	121	12	157	73	48	17519	**0.81**
	MIS	0	0	9244	2962	151	176	418	1878	85	14914	**0.62**
	RIC	1127	0	3344	166501	3635	897	3320	2393	503	181718	**0.92**
	SUG	0	0	91	2738	2502	73	394	85	24	5906	**0.42**
	CAS	0	0	67	176	460	588	1866	394	91	3641	**0.16**
	RUB	0	0	224	1084	2326	1163	6076	1109	170	12152	**0.50**
	EUC	85	0	4301	3374	545	806	927	9692	412	20142	**0.48**
	OTH	0	0	624	1969	485	279	309	503	479	4646	**0.10**
Total		14502	14223	18361	182718	10389	4259	14151	16441	1932	276975	
Producer's Accuracy		**0.92**	**1.00**	**0.50**	**0.91**	**0.24**	**0.14**	**0.43**	**0.59**	**0.25**		
Overall Accuracy		**0.80**										

Appendix Table 4.10 The accuracy of the reality map and simulated map for 2015 of LMSW from Dyna-CLUE

		Reference map 2015										
	Land use	**FOR**	**URB**	**MIS**	**RIC**	**SUG**	**CAS**	**RUB**	**EUC**	**OTH**	**Total**	**User's ACC**
Simulation map 2015	**FOR**	8134	0	6	19	0	50	44	168	7	8429	**0.97**
	URB	63	12100	151	2782	586	303	277	181	522	16964	**0.72**
	MIS	125	548	12146	6922	308	258	447	3212	405	24372	**0.50**
	RIC	3954	1408	5020	163725	5834	568	2177	1477	486	184649	**0.89**
	SUG	2108	31	334	107	1883	1243	2793	464	169	9133	**0.21**
	CAS	38	38	31	56	359	177	1459	84	0	2242	**0.08**
	RUB	69	174	50	2573	819	429	3982	226	66	8389	**0.48**
	EUC	88	187	555	3568	296	1073	2548	10268	199	18782	**0.54**
	OTH	0	44	76	3832	19	0	0	0	45	4015	**0.01**
Total		14580	14530	18370	183584	10106	4101	13727	16080	1898	276975	
Producer's Accuracy		**0.56**	**0.83**	**0.66**	**0.89**	**0.19**	**0.04**	**0.29**	**0.64**	**0.02**		
Overall Accuracy		**0.77**										

(FOR=Forest, URB=Urban, MIS=Miscellaneous, RIC=Rice, SUG= Sugarcane, CAS=Cassava, RUB=Rubber, EUC=Eucalyptus, OTH=Other Agricultural)

Acronyms

ABM	Agent-Based Model
ASCII	American Standard Code for Information Interchange
MLP	Multi-Layer Perception
CA	Cellular Automata
CA-Markov	Cellular Automata - Markov
CGEs	Computable General Equilibrium
CLUE	Conversion of Land Use and its Effects
Dyna-CLUE	Dynamic Conversion of Land Use and its Effects
DEM	Digital Elevation Model
DPA	Department of Provincial Administration
DPSIR	Drivers Pressures State Impact Response Framework
EEA	European Environment Agency
FAO	Food and Agricultural Organization of the United Nations
GI	Geographical Indications
GIS	Geographic Information System
IIASA-LUC	International Institute for Applied System Analysis - Land Use Change
IMAGE	Integrated Model to Assess the Global Environment
LCM	Land Change Modeller
LDD	Land Development Department
LMSW	Lam Mun sub-Watershed
LUDAS	Land Use Dynamic Simulator
LULUCF	Land Use, Land-use Change and Forestry Dynamic
MCE	Multi-Criteria Evaluation
MCSW	Mae Chan sub-Watershed
LCM	Land Change Modeller
ROC	Relative Operating Characteristic
SALU	Sahelian Land Use Model
SLEUTH	Slope Land use Exclusion Urban Transportation Hill shading
UTM	Universal Transverse Mercator coordinate system

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