Modelling Deforestation in Dzalanyama Forest Reserve, Lilongwe, Malawi: Using Multi-agent Simulation Approach

January 2013

Kondwani Godwin MUNTHALI

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A Dissertation Submitted to
the Graduate School of Life and Environmental Sciences,
the University of Tsukuba
in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy in Science
(Doctoral Program in Geoenvironmental Sciences)

Kondwani Godwin MUNTHALI

Abstract

Several parameters are recognized to influence agents of deforestation's decision-making to deforest. Physical environment strongly influences deforestation, and in the tropics, it is evident that many of these parameters hinge on agricultural activities. Dzalanyama forest reserve designated boundary covers 93,500 hectares (ha) and with increased urban demand for charcoal, there are marked land cover transitions in the forest reserve. Observed trends indicate that the forest cover as of 1990 was 65, 775 ha of which 22,031 ha were lost by the year 2010.

The objective of this study is therefore to derive understanding of the underlying causes of deforestation in Dzalanyama and estimate the future of forest cover loss. This study is further aimed at providing a socio-scientific basis for potential policy intervention scenarios towards sustainable management efforts of the forest reserve. I describe the development of a multi-agent simulation (MAS) to simulate the selections of cropping decisions and a competing labour practice (charcoal production) by smallholder farmers surrounding the forest reserve.

The deforestation trends for Dzalanyama forest reserve were simulated over a 40-year period beginning the year 1990. Occupying a single grid cell (100x100m = 1ha), relocation of the kiln is the emergent phenomenon. It emerges from the households demand to produce charcoal after failing to grow enough food while where it relocates to is determined by the biophysical factors of distance to road, river and forest/settlement edge. The former determined the quantity accuracy while the latter the spatial accuracy. In the business as usual scenario (S_1) 12, 207 ha of forest were simulated as lost against 13, 639 ha observed in 2000. The quantities accumulate to 19, 459 ha simulated against 22, 031ha observed by the year 2010.

From the supply end, this massive forest loss is evident in the area from the combined influence of: 1) the households' inability to meet their food and/or cash requirements from agriculture, their main activity, due to among other factors population growth and poverty; and

2) the households' engagement in charcoal production (deforestation) as a coping mechanism against the resulting food and/or cash deficiencies of (1) above. Based on the successful simulation for 2000 and 2010, I predicted future forest loss for 2020 and 2030 under S_1 and an increased reward from charcoal production scenario (S_2). S_1 conditions predict forest loss of 23, 100ha by the year 2020 that accumulates to 26,721 ha in 2030. S_2 reduces the predicted forest loss to 21,676 ha in 2020 and 24,060 ha in 2030.

The individual decision-making based on household composition, availability of production materials (hybrid seed and organic fertilisers), access to subsidized production materials and access to sustainable farming methods contributes significantly to quantities of deforestation with road, river and forest/settlement boundary determining where exactly the deforestation takes place. The results in S_1 show close similarities with forest loss trends observed in Dzalanyama between 1990 and 2010 and provide a good basis to predict forest cover for 2020 and 2030. Food deficiency in the smallholder farming system is the major driving factor of quantities of deforestation in Dzalanyama and the future looks bleak in the business as usual scenario.

With financial resources for sustainable interventions being a major problem, S_2 tests the overall influence on the deforestation levels if the charcoal production industry is allowed to generate finances for its own sustainable management. The critical assumption being that the smallholder households (just as in S_1) will continue farming as their main traditional economic activity and not abandon the crop production and shift significantly towards charcoal production. The results of S_2 show a positive and sustainable trend to control the deforestation. When compared to S_1 estimates of 2020 and 2030 respectively, the accumulated forest loss decreased by 6 % in 2020 and 10 % in 2030. This reduction in forest loss represents an accumulated gain (or sustenance) of forest cover of 4 % in 2030 which can only increase in the years beyond.

To achieve S_2 the study, therefore, proposes formalisation of the charcoal production process, which has the advantages to not only reduce deforestation as established in this study but also has great potential for improved revenue collection by government through a formalised taxation system. This has the potential of making more financial resources available to the charcoal producers and forestry authorities. In the end, the forestry authorities would then have the financial capacity to enforce further and better sustainable forest management interventions. Again, with more disposable cash available, the charcoal producers can then begin to invest in better agricultural farming practices to increase crop production or better and efficient charcoal production techniques to reduce wastage of fuel wood. The former would significantly reduce household dependency on charcoal production while the latter would imply cutting fewer trees to sustain the households' needs. Either way the increased reward from charcoal production for the producer serves to reduce the deforestation in the long term.

Keywords: multi-agent simulation, agent based simulation, tropical deforestation, farm-based decision-making, computer modelling and sustainability

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Abbreviations / Acronyms

MAS	Multi-Agent Simulation
FISP	Farm Input Subsidy Program
EPA	Extension Planning Area
GDP	Gross Domestic Product
GIS	Geographical Information Systems
LUCC	Land-Use/-Cover Change
RS	Remote Sensing
CA	Cellular Automata
CM	Cellular Model
CAS	Complex Adaptive Systems
IGA	Income Generating Activities
DoF	Department of Forestry
EW	Extension Worker
ADD	Agricultural Development Division
ADMARC	Agricultural Development and MARketing Corporation
HIV/AIDS	Human Immunodeficiency Virus / Acquired Immuno Deficiency Syndrome
D-MAS	Dzalanyama-Multi-Agent Simulation
FHA	Farm Household Agent
MWK	Malawi Kwacha

Chapter 1

Introduction

1.1 Purpose of the research

Since independence, in 1964, agriculture has continued to play a central role in defining Malawian rural livelihoods. It employs over 85 % of the rural population, normally accounts for 35–40 % of Gross Domestic Product (GDP), and contributes over 90 % to total export earnings (Government of Malawi, 2007a). Tobacco is the major export earner and contributes approximately 65 % of the country's export earnings, followed by tea at 8 % and sugar at 6 %. Maize is the major food crop, cultivated on over 60 % of the arable land (Tchale, 2009). The agricultural sector in Malawi is categorized into estate agriculture sector and smallholder sector, with the latter accounting for 60 % of agriculture GDP (Chirwa and Matita, 2012). Recent estimates indicate that 55 % of smallholder farmers have less than 1 hectare of cultivatable land (Government of Malawi, 2002). Smallholder agriculture remains an important source of livelihood for a majority of the rural population. For instance, approximately 84 % of agriculture value-added comes from 1.8 to 2 million smallholder farmers who on average own only 1 hectare of land (World Bank, 2003). Most smallholder farmers in Malawi still cultivate using hoe technology and rely heavily on family labour. Most of smallholder farming is focussed on producing food staples such as maize and rice. Alwang and Siegel, (1999) estimate that 70 % of Malawian smallholder farmers cultivate 1.0 hectare with the median area cultivated being 0.6 hectares, and devote 70 % of the land to maize, the main staple food. Others estimate that only about 15 % of the maize that is produced in the country is marketed, while the rest is used to meet subsistence needs (Chirwa and Matita, 2012).

With the majority of the population living in rural areas in Malawi, both wage employment and chances of escaping poverty based on smallholder agriculture are currently very limited (Norad, 2009). High population growth continues to exert pressure on natural resources. As such both customary land and protected forest areas are over-exploited for firewood, timber, charcoal and curios, for use in homes or for sale at roadside or in towns and cities. This serves to worsen the state of forest cover leading to tropical deforestation such that policy makers, scientists, and the public are increasingly concerned. Its negative consequences include climate change, biodiversity loss, reduced timber supply, flooding, siltation, and soil degradation (Kaimowitz and Angelsen, 1998). Efforts have since been scaled up to model the questions of why, where, when, and how much forest is converted to other land uses. There is a plethora of models focusing mainly on describing how and why landholders behave the way they do, and the linkages between their decisions and the rest of the economy (Kaimowitz and Angelsen, 1998). However, those that seek to assess the linkages between the decision made by the smallholder agriculture landholders and deforestation in particular are limited (Munthali and Murayama, 2012). Kaimowitz and Angelsen, (1998) define deforestation as "situations of long term removal of forest cover". Many tropical activities are recognized as leading to deforestation, including logging, shifting cultivation, and collecting fuelwood, among others. In tropical sub-Saharan Africa, collecting fuelwood is the major source of deforestation.

A wide array of simulation approaches have been employed to enhance human understanding of the mechanisms driving tropical deforestation, including analytical and statistical equation-based (differential sets or not) mathematical models such as linear programming. However, apart from the limited levels of complexity that can practically be built into them, these models have downplayed the influence of individualistic decision-making and social phenomena (Parker *et al.,* 2003).

Tropical deforestation is a complex environmental problem often comprising several micro interacting spatial subsystems. For a long time, deforestation modelling has lacked an explicit spatial dimension largely because of its multidisciplinary and temporal dynamism, despite being spatial in nature. Data from remote sensing have helped to monitor dynamically changing systems although future estimates of such changes are hard to make. Again the nature of the interactions between these systems often makes it difficult to predict the outcomes that will result from, for instance, particular management actions and policies. Researchers have since utilized a variety of tools to explore the dynamics of these complex systems and the potential outcomes associated with proposed new policies and/or changes in the human or natural systems in question. Such tools, from statistical and mathematical models to geographic information systems (GIS) and dynamic models, have proven to be helpful in understanding complex geographic phenomena. Of late multi-agent simulation (MAS) techniques have been widely used in land-use/-cover change (LUCC) modelling with very satisfactory results (Deadman *et al.,* 2004; Parker *et al.,* 2003; Wada *et al.,* 2008). Building on their sensitivity to small individual changes, MASs have demonstrated great potential to magnify micro-scale decisions made at the individual farm level thereby exposing the trigger mechanisms of LUCC and deforestation in particular.

Smallholder farmers in Malawi experience several challenges as they strive to sustain food production with far reaching consequences that extend beyond the agricultural frontiers. Consequently, sustainability of the natural resources near the smallholder communities is threatened. The objective of this study is to derive understanding of the underlying causes of deforestation in Dzalanyama and estimate the future of forest cover loss. I seek to provide a socio-economic and scientific basis for potential policy intervention scenarios towards sustainable management efforts of the forest reserve. This study describes the development of MAS to simulate the selections of cropping decisions and a competing labour practice (charcoal production) by smallholder farmers surrounding the forest reserve. This is a simulation of the inefficiencies of the smallholder crop production theories being practiced at the individual farming households and how they translate into deforestation. By capturing the smallholder farmers’ interactions with the land-use system and surrounding environment, this MAS research hopes to provide insightful and deeper understanding of the agricultural and environmental implications in management of land and forest resources to avoid irreversible damages caused by deforestation in Dzalanyama and surrounding areas.

1.2 Structure of the research

This dissertation is organised into six chapters. Figure 1-1 shows the research framework and outlines the interrelationships of the chapters. In chapter 1, I introduce the research objective and a brief outline of the research structure. Chapter 2 provides the theoretical framework of the simulation approach chosen for this study while Chapter 3 highlights the situation in the study area. Chapter 4 quantifies the extent of the deforestation in Dzalanyama. Chapter 5 presents the data and describes the simulation approach. I then present the results and discuss the influence of the selections of cropping decisions and the competing labour practice (charcoal production) on forest loss. A summary and conclusion is then provided in Chapter 6.

The introductory chapter (Chapter 1) is a general overview of the research. It highlights the existing deforestation problems, the essence of simulation for the area, the main objectives and simulation method adopted.

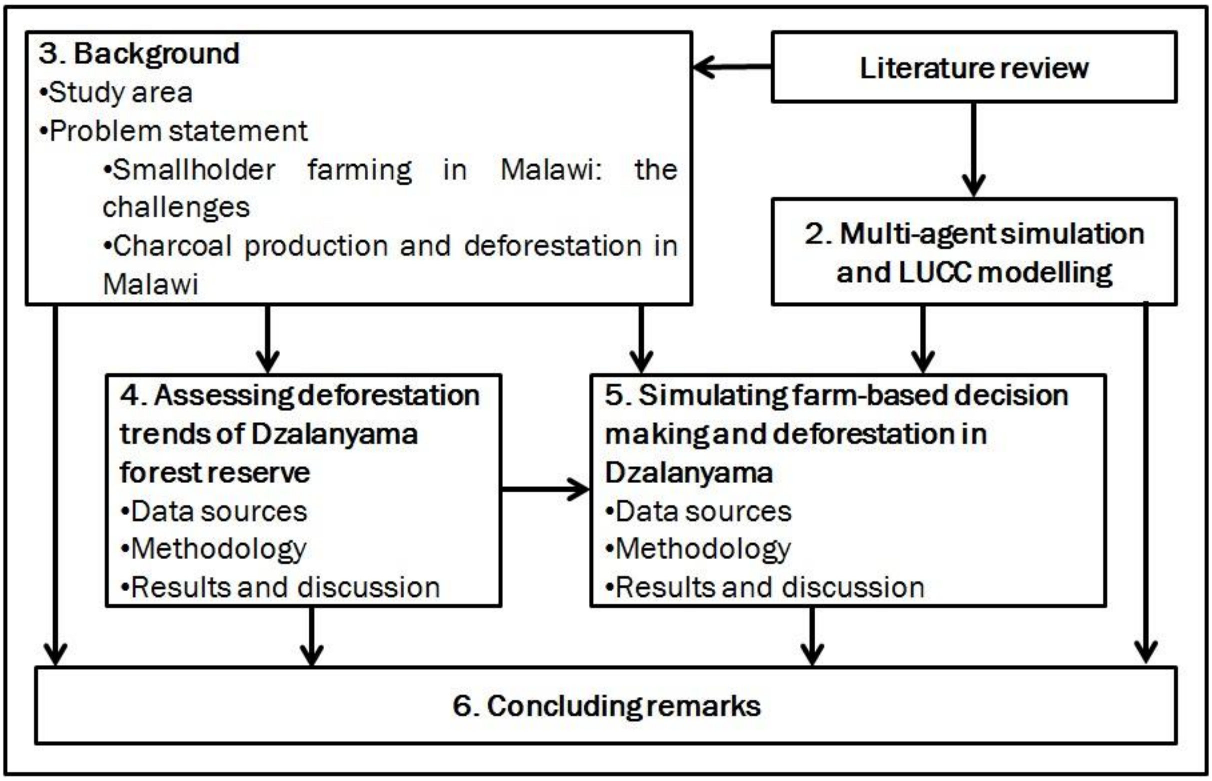

Figure 1-1: Research framework

Note: The number in each box corresponds to a dissertation chapter.

Chapter 2 discusses the theoretical and methodological issues that are relevant to this research. The theoretical section discussed MAS approaches in LUCC in general. It starts with historical background of MAS, its structure all the way down to implementation platforms available. It also shades more light on the shortfalls of current multi-agent techniques in handling LUCC in general and tropical deforestation in particular. This discussion then lays a foundation for a proposed extension of LUCC MAS to tropical deforestation with a specific focus on simulating the individual farm-based decision-making of the smallholder farming households in the study area.

Chapter 3 is a detailed presentation of the geographic, biophysical and social attributes of the study area. It also expounds on the problem of deforestation in Dzalanyama forest reserve by digging deeper into the land, labour and resource-availability challenges facing the smallholder farmers in Malawi and in the study area. I also discuss how charcoal production is becoming the easy way out for most households in case of food shortages.

Chapter 4 is an analysis that quantifies the LUCC for the study area using multispectral classification, remote sensing (RS), GIS and Markov Chain analysis techniques. Multi-temporal RS data were used to map land-use/-cover distribution. The results of the LUCC and forest loss of Dzalanyama forest reserve are presented and factors influencing the forest loss discussed.

Chapter 5 looks at the deforestation trends of Dzalanyama by simulating the individual farm-based decision-making of the farming households. The MAS methodology is discussed in detail and both the biophysical and socio-economic data sets preparations are described. In this chapter the results of the deforestation simulation are presented with keen observation of the results under the business as usual scenario and in comparison with other scenarios. This serves to derive understanding of the impact of the selections of cropping decisions and the competing labour practice (charcoal production) on forest loss and devise possible ways of curbing the same. Sub-section 5.5 discusses the findings of the study in relation to the research objectives.

Chapter 6 then summarises and concludes the research findings. The simulated results indicate worsening deforestation trends with huge hectares of the forest cover converted to other land uses. As a mitigating factor, the simulation results points to a positive influence on deforestation, a regularised charcoal production in the study area would have. The deforestation was noted to be highly influenced by existing road and river networks and more so the physical distance from the forest edge/settlement boundary.

Chapter 2

Multi-agent simulation and LUCC modeling

2.1 Introduction

There is a wide array of simulation methods that mimic the mechanisms of human intelligence to achieve one or more objectives. Analytical simulation approaches use equations that explain data, while statistical ones work primarily with probabilities (Munthali, 2012). An iterative combination of any or both of the above uses feedback options to answer problems, which are too complex to be solved by one equation. Most of these equation-based mathematical models identify system variables, and evaluate or integrate sets of equations relating to these variables. A variant of such equation-based models are based on linear programming (Howitt, 1995; Weinberg *et al.,* 1993), and are potentially linked to GIS information (Chuvieco, 1993; Cromley and Hanink, 1999; Longley *et al.*, 1994).

However, in practice there are limited levels of complexity that can be built into these models (Parker *et al.*, 2003). To incorporate complexity, sets of differential equations linked through intermediary functions and data structures are sometimes used to represent stocks and flows of information (Gilbert and Troitzsch, 1999). Although they include human and ecological interactions, these systemic models tend to have difficulties in accommodating spatial relationships (Baker, 1989; Sklar and Costanza, 1991). Apart from their power and ease of use, statistical simulation approaches have been widely accepted largely because they include a variety of regression techniques applied to space and more tailored spatial statistical methods (Ludeke *et al.,* 1990; Mertens and Lambin, 1997). However, according to Parker *et al.*, (2003), unless tied to theoretical frameworks, statistical models tend to down-play decision-making and social phenomena. Other simulation approaches express qualitative knowledge in a quantitative fashion by combining expert judgement with probability techniques such as Bayesian or artificial intelligence approaches (Parker *et al.*, 2003).

The gaps and inconsistencies left by these mathematical modelling approaches saw the proliferation of cellular automata (CA) in combination with Markov Chain models as an alternative (Munthali and Murayama, 2012). In CA, each cell exists in one of a finite set of states, and future states depend on transition rules based on a local spatio-temporal neighbourhood (Kamusoko *et al.,* 2009), while in Markov models, cell states depend probabilistically on temporally lagged cell state values (Munthali, 2012). These cellular models (CMs) underlie many LUCC studies in which Markov–CA combinations are common (Balzter *et al.,* 1998; Li and Reynolds, 1997; Kamusoko *et al.,* 2009). CMs assume that the actions of human agents are important, and others assume a set of agents coincident with lattice cells and use transition rules as proxies to decision-making, and as such they both fail to simulate decisions expressly and explicitly (Parker *et al.*, 2003). In the latter case, the actor is not tied to locations and, as Hogeweg, (1988) observed, this introduces problems of spatial orientation to the extent that the intrinsic neighbourliness of CA relationships do not reflect on the actual spatial relationships. This highlights the main challenge faced by CMs and most of the aforementioned modelling approaches when it comes to incorporating individualistic human decision-making (Parker *et al.,* 2003). When the focus is on human actions, agents become the crucial components in the model. While cellular models are focused on landscapes and transitions, MASs primarily focus on humans and their actions. Therefore, it is not surprising to realise that a MAS is more of a mindset that builds on describing a system from the perspective of its constituent units than a technology (Munthali, 2012).

The benefits of the MAS method over other LUCC modelling techniques can be summarized in that: (i) it captures emergent phenomena; (ii) it provides a natural description of a system; and (iii) it is flexible (Munthali and Murayama, 2012). It is clear, however, that the ability of MAS to deal with emergent phenomena is what drives the other benefits (Bonabeau, 2002). In a geographical context of level and scale, Auyung, (1998) understands ‘emergence’ as emergent phenomena at one level that constitute the units of interaction, or drivers of change, at a higher level. There is little doubt that tropical deforestation is an emergent phenomenon. It not only results from the sum of individual actions of smallholder farmers’ decision-making in the tropics, but also because of the interactions among them. It is, therefore, rather natural that MAS should be used to elevate human understanding of the trends in LUCC in general and tropical deforestation in particular.

While I acknowledge implementation of agent-based LUCC models in other spatial units of analysis, for instance in using parcels and buildings (Waddell *et al.,* 2010) and irregular spatial units at a cadastral scale (Jjumba and Dragi´cevi´c, 2011), this chapter's review is limited to applications that used grid cells as a unit of spatial analysis. This is because satellite data are widely available and routinely collected in tropical regions, making raster-based approaches the most prudent. Again, availability of statistical data based on vector representation is very limited in these regions (Munthali and Murayama 2012).

There is a large body of literature discussing the application of MASs to a number of global environmental challenges. Agents have been used to represent several types of entities, including atoms, biological cells, animals, people, and organizations (Liebrand *et al.,* 1988, Epstein and Axtell, 1996, Conte *et al.,* 1997, Weiss, 1999, Janssen and Jager, 2000). A general review of MAS in LUCC has been provided by Parker *et al.,* (2003). Its use has largely been an observation and then a simulation of human behaviour and its effects on land-use/-cover (LUC) on the pieces of land where humans reside. However, what happens when the actions of an agent in one place affect and change the LUC in another place? More concretely and specifically, what sorts of thresholds underlie deforestation trends caused by agents acting from a distance and how are they reached? This review, therefore, adds to the discussion of MASs in LUCC by exploring the extent to which smallholder farming activities at farm level in rural tropical regions influence LUC patterns beyond agricultural boundaries, and more specifically, the deforestation of protected areas. I do this in the knowledge that (i) while deforestation trends in protected areas continue to worsen, this is happening even in areas where no significant shifts in cultivation or expansion of agricultural land are perceived; (ii) it has been established that a wide selection of the nutritive requirements for survival in smallholder households are taken directly from forested environments, rather than from the limited-scope agricultural activities in which the households are engaged (Walker 1999); and (iii) smallholder agriculture is the main activity of the majority of households in these areas.

The rest of the chapter starts by presenting a brief historical background and a description of the mechanism of MAS in general in sub-chapter 2.2. Sub-chapter 2.3 lists a selected set of MAS efforts in tropical smallholder agricultural environments that attempted to develop the understanding of the deforestation process, either explicitly or in the context of other issues. Then in sub-chapter 2.4, I discuss the methodologies adopted and how they relate to cases of deforestation as one aspect of LUCC by expounding on the specific criterion chosen for each selected paper. This forms a basis for a more general discussion comparing the criteria and a reflection on the lessons learnt.

2.2 Multi-agent simulation mechanism

2.2.1 History of multi-agent simulation

MAS can be traced back hundreds of years to discoveries that include Adam Smith's invisible hand in economics, Donald Hebb's cell assembly, and the blind watchmaker in Darwinian evolution (Axelrod and Cohen, 2000). In each of these early theories, simple individual entities interact with each other to produce new complex phenomena that seemingly emerge from nowhere (Heath, 2010). Newton's reductionist philosophy (Gleick, 1987) lacked tools to adequately study and understand emergent phenomena. However, when the theoretical and technological advances were made leading to the invention of the computer, scientists began building models of these complex systems and began to have a better understanding of their behaviour (Munthali and Murayama, 2012). The pioneering work was carried out by Alan Turing with the invention of the Turing machine around 1937. By replicating any mathematical process, the Turing machine showed that machines were capable of representing real-world systems (Heath, 2010). The theoretical scientific belief that machines could recreate the non-linear systems observed in nature got a further boost when Turing and Church later developed the Church–Turing hypothesis. It stated that a machine could duplicate not only the functions of mathematics, but also the functions of nature (Levy, 1992). Premised on von Neumann's heuristic use (von Neumann, 1966) these machines have since moved from theoretical ideas to the real computers that we are familiar with today (Heath, 2010).

Now that computers had come to stay, the scientific focus shifted towards synthesizing the complexity of natural systems. Influenced by a reductionist philosophy, most scientists took a top-down approach (Munthali, 2012). Evidence of this is seen in early applications of artificial intelligence, where the focus was more on defining the rules of the appearance of intelligence and creating intelligent solutions than focusing on the structure that creates intelligence (Casti, 1995). This approach was skewed towards the idea that systems are linear, and thus it failed to enhance our understanding of the complex non-linear systems found in nature (Langton, 1989). A mile stone was reached when Ulam suggested that von Neumann's self-reproducing machine could be represented more easily by using CA (Langton, 1989). CA are self-operating entities that exist in individual cells which are adjacent to one another in a 2D space like a checkerboard, and have the capability to interact with the cells around them (Munthali, 2012). According to Heath, (2010), the influence of the CA approach was overwhelming for two reasons: (1) because the cells in CA act autonomously and simultaneously with other cells in the system, the simulation process changed from serial to parallel representation; and (2) CA systems are composed of many locally controlled cells that together create global behaviour. The former was important because many natural systems are widely accepted to be parallel systems (von Neumann, 1966), while the latter led to the bottom-up approach as the CA architecture requires engineering a cell's logic at the local level in the hope that it will create the desired global behaviour (Langton, 1989).

After learning how to synthesise complex systems and discovering some of their properties using CA, complex adaptive systems (CASs) began to emerge as the direct historical roots of MASs (Heath, 2010; Munthali, 2012). Drawing much of its inspiration from biological systems, CASs were mainly concerned with how complex adaptive behaviour emerges in nature from interactions among autonomous agents (Dawid and Dermietzel, 2006). Much of the early work in defining and designing CASs resulted from work to identify properties and mechanisms that compose all MASs as we know them today (Buchta *et al.*, 2003). Heath, (2010) reported the three main properties of CASs to be aggregation, non-linearity, which is the idea that the whole system output is greater than the sum of the individual component outputs, and diversity, meaning that agents do not all act the same way when stimulated by a set of conditions.

It is evident that MASs emerged from the scientific search to try and understand non-linear systems, and this revelation suggests why MASs are a useful research tool. In summary, many subject areas played an important role in developing the multidisciplinary field of MASs (Munthali, 2012).

2.2.2 Multi-agent simulation structure

Parker and Meretsky, (2004) noted that MASs often model complex dynamic systems and focus on the macro-scale, or "emergent," phenomena that result from the decentralised decisions of, and interactions between, the agents. The concept behind MASs, which was borrowed from the computer sciences, is to mimic human- or animal-like agents interacting at the micro-scale in a computer simulation in order to study how their aggregation leads to complex macro-behaviour and phenomena (Berger, 2001).

MASs build on a successful specification of the agent itself, its behaviour, the representation of the environment and the interactions. The term agent refers to any individual or group of individuals who exist in a given area and are capable of making decisions for themselves or for the given area (Munthali, 2012). Generally, an agent can represent any level of organization (a herd, a village, an institution, etc.) (Verburg, 2006). In LUCC modelling, these agents couple a human system making land-use decisions with an environmental system represented by a raster grid (Deadman *et al.*, 2004, see Figure 2-1).

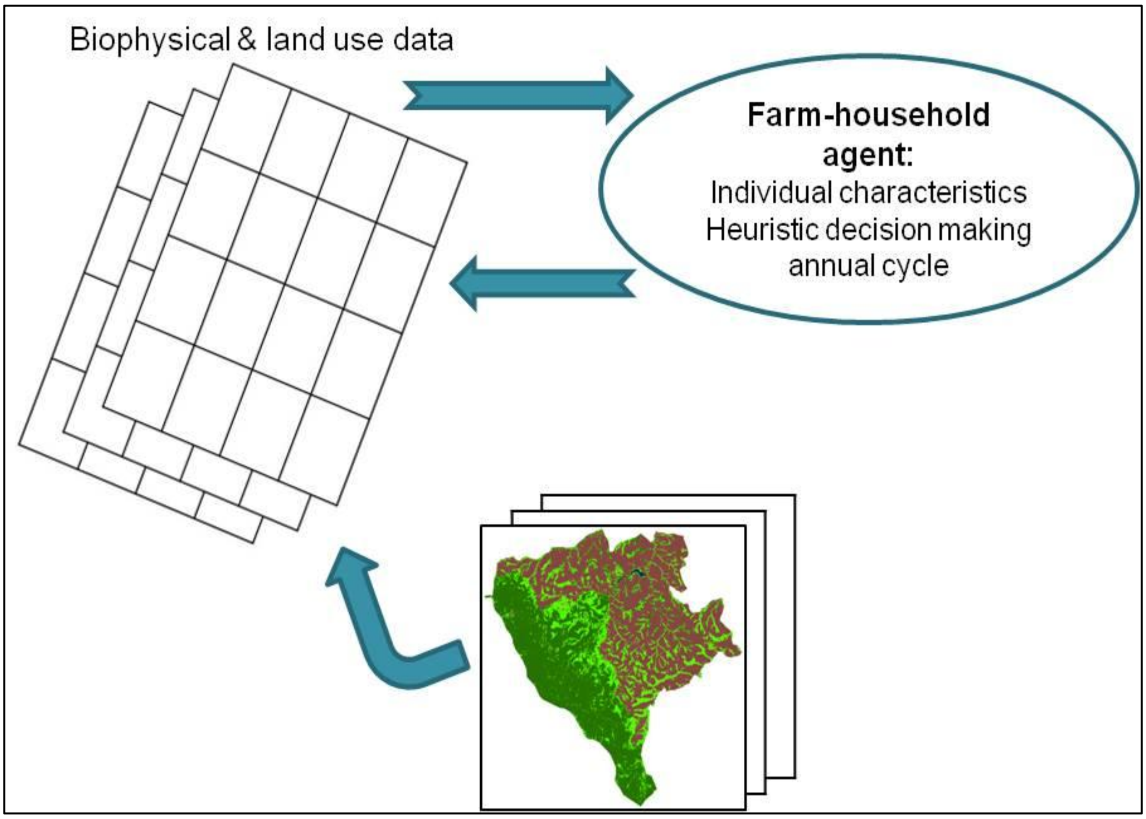

Figure 2-1: A conceptual framework for a farm-based decision-making MAS

(Source: Munthali, 2012)

The specification of the behaviour of agents demands a proper description of the actual actions of the agents and the basic elements that cause modifications in their environment and in other agents (Bandini *et al.,* 2009). It also demands the provision of mechanisms for the agents to effectively select the actions to be carried out. The mechanism of an agent refers to the internal structure which is responsible for the selection of actions (Russel and Norvig, 1995). The actions of agents pertain to descriptions of the agents' actions, for instance state transformation, environmental modifications, an agent's perception and responsiveness, and the spatial physical displacement of an agent in the environment (Munthali and Murayama, 2012). The description of the environment of an agent should, among other factors, primarily define and enforce the rules of behaviour of an agent, and maintain the internal dynamics of the system to avoid chaos (Munthali, 2012). At the same time, it should also support an agent's perception and localised actions by embedding and supporting access to objects and parts of the system that are not necessarily modelled as agents (Bandini *et al.,* 2009). Interaction is a key aspect in agent design, both with other agents and/or the environment. Several definitions of interaction have been provided, and most of them focus on the ability of agents to engage with the environment and with other agents in a meaningful problem-solving or goal-oriented scheme to achieve particular objectives according to the coordination, cooperation and competition practices of natural phenomena (Munthali and Murayama, 2012).

These concepts have been the subject of experiments on many platforms, the choice of which tends to depend largely on the researcher's preference, the computation requirements, and the overall objectives of the study (Munthali, 2012). Most MAS platforms follow the "framework and library" paradigm (Railsback *et al.,* 2006). A framework is a set of standard concepts for designing and describing MASs, while a library is a set of software implementing the framework and providing simulation tools (Munthali, 2012). Without trying to be exhaustive, this section presents some of the commonly available agent modelling platforms.

The earliest of these platforms include the Swarm (Minar *et al.*, 1996, www.swarm.org), whose libraries were written in Objective-C with later updates using Java Swarm in order to allow the use of Swarm's Objective-C library in Java (Railsback *et al.*, 2006). The recursive porous agent simulation toolkit (RePast) (Collier, 2000; http://repast.sourceforge.net/) was first developed as a Java implementation of Swarm, but has since evolved into a fully-fledged stand-alone Java platform. MASON (Luke *et al.*, 2005; http://cs.gmu.edu/~eclab/projects/mason/) was developed later, also as a Java implemented tool. Despite these platforms providing standardised software designs and tools without limiting the type or complexity of the models they implement, they have well-known limitations (Railsback *et al.*, 2006). According to Tobias and Hofmann, (2004), their weaknesses include difficulty of use, insufficient tools for building models, and especially tools for representing space, insufficient tools for executing and observing simulation experiments, and a lack of tools for documenting and communicating software. The Logo family evolved from such limitations with the aim of providing a high-level platform that allows model building and learning from simple MASs (Railsback *et al.*, 2006). Although built on elementary-level principles primarily to aid student learning, NetLogo (http://ccl.northwestern.edu/netlogo/) now contains complex capabilities and is arguably the most widely used platform (Railsback *et al.*, 2006). Figure 2-2 is a screenshot of a NetLogo platform that comes with its own programming language, which is claimed to be simpler to use than Java or Objective-C, an animation display automatically linked to the program, and optional graphical controls and charts (Munthali, 2012).

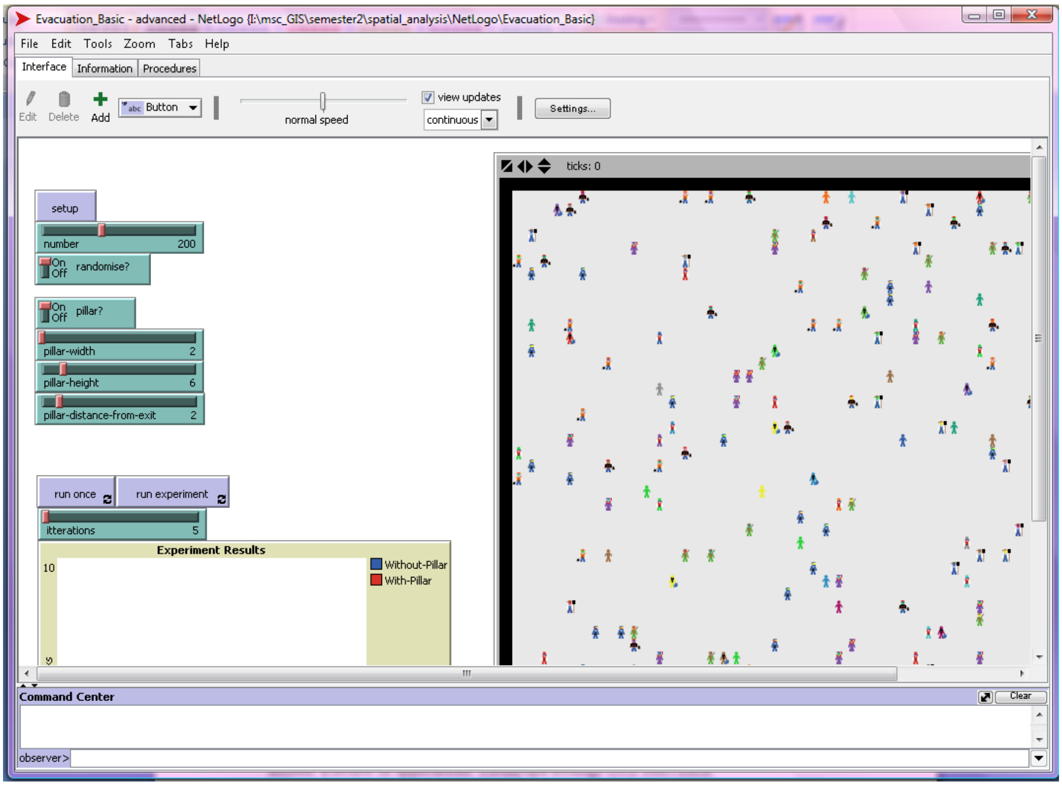

Figure 2-2: A NetLogo MAS platform (Source: Munthali, 2012).

2.3 Applications of Multi-agent simulation farm-based deforestation

Smallholder agriculture continues to be the mainstay activity in many tropical regions of the world; however, opinions vary about its influence on deforestation. The introduction of monetary economies and increases in population has led to a shift to more profit-oriented agricultural practices and/or high demand for food in these regions. These have resulted in greater intensification of agricultural land use, including shorter shifting-cultivation fallow periods and extended cultivation periods, and in the exploitation of forested areas (Munthali and Murayama, 2012). However, a significant level of variability still exists in these land-use systems. This variation generally stems from the differing aspirations, attitudes, and resources among farming households (Mathews *et al.,* 2007), such that neither population nor poverty alone constitutes the major underlying causes of deforestation and LUCC in general (Lambin *et al.,* 2001).

There is a well-developed set of models that formally link socioeconomic factors to land-use allocation in a nonspatial context. The gap between descriptive analysis and nonspatial models has since been bridged, to an extent, by spatially explicit simulation models (Parker and Meretsky, 2004). Just as the empirical illustration of observed outcomes has been a sufficient end unto itself for MASs (Epstein, 1999), it has also been argued that it is retrogressive to limit the potential and appropriateness of MASs to such illustrations (Parker *et al.,* 2003). Therefore, to understand how farm-based decisions influence deforestation beyond the farms, it is important to explore how decisions have an influence beyond agricultural boundaries. Table 2-1 presents a selected set of MAS efforts to improve our understanding of the influence of smallholder agricultural practices on deforestation. I acknowledge that the primary objective of some of the selected papers was not deforestation in particular but LUCC in general; however, I still opted to include them because (i) at the time of writing this chapter there was no known, at least as far as the authors were aware, MAS work specifically tackling tropical deforestation from the perspective of smallholder farming practices; (ii) the selected papers touched either on tropical deforestation or on individual farm-based decision-making, or both; and (iii) the modelling approach was fully MAS (Munthali and Murayama, 2012).

Table 2-1: Summary description of selected review papers

Author (s)	Location	Agent unit	Farmer activities	Objective
Deadman *et al.*, (2004)	Altamira, Brazil	Farmer household	Colonist household farming	Simulate Amazon deforestation trends
Macmillan and Huang, (2008)	Artificial society	Farmer (s)	Sub-commercial farming	Land use change simulation
Rajan and Shibasaki, (2000)	Thailand	Grid based (group of) individual(s)	Shifting cultivation	Land use change simulation
Sulistywati *et al.*, (2005)	Indonesia	Farmer household	Swidden cultivation	Simulate impacts of cash cropping in swidden agricultural systems
Wada *et al.*, (2007)	Luangprabang, Lao PDR	Village cluster	Paddy shifting cultivation	Simulate shifting cultivation trends
Walker, (1999)	Brazil	Farming groups (20 persons)	Smallholder rotational farming	Description of market-context extra-marginal decision-making

(Source: Munthali and Murayama, 2012)

2.3.1 Problems of MAS implementations in tropical deforestation

Underscoring the sporadic, incomplete, and mostly non-existent market context in smallholder agriculture, Walker, (1999) accounted for land allocation beyond the extensive margins of permanent agriculture. He built on the notion of peasantry, whereby smallholder farmers require a wide selection of natural commodities to survive and pursue cultural activities. Though I agree with Walker, (1999) that tropical forests are subject to the influences of purposeful economic activity and the implied direct occupation of forest land through shifting cultivation, I beg to differ on its universality and representativeness. While it may be true that, in the absence of a smallholder market, farmers do obtain a reasonable number of survival commodities from the forest (Walker, 1999), the tropical story does not end there. Peasantry land-use systems persist even in the face of advances in agricultural technology (Ellis, 1993), such that when populations grow, pressure mounts not only on the land, but also on the production theories involved. In the case of shifting cultivation, this pressure is eased by relocation, but where land is scarce, the linkages between household production theories and the realms of protected tropical forests need to be well articulated. So far, in these contexts of land scarcity, the influence on deforestation trends of the choices made in smallholder crop production is far less known. Walker, (1999) echoed this when he proposed a further extension of his model.

Wada *et al.*, (2007) developed a micro-scale MAS to simulate the spatial and temporal patterns of shifting cultivation in a mountainous region in Laos. The aim was to understand how shifting cultivation expands in space. Similarly, Rajan and Shibasaki, (2000) modelled how farmers determined types of crops, expansion or contraction of farming areas, and relocation of settlements, by referring to the collective household income from agricultural and non-agricultural revenues in Thailand. While MASs can incorporate the fact that human decision-making is heterogeneous, decentralized, and autonomous (Parker *et al.*, 2003), the model of Wada *et al.*, (2007) represents a case where individual behaviour is conspicuously less heterogeneous and decentralized. In both cases, the biophysical attributes of climate, soil properties, and water and nutrient stresses on agricultural productivity are explicitly considered in the context of a farmer/agent relocating or expanding acreage. The emphasis is on the agent's ability to transform each grid of land unit where it is found, on the basis of the demographic and biophysical conditions. First, the ability to 'transform' assumes among other things that (i) possibilities of technological intensification of agricultural practices do exist and (ii) there is still available land to which the farmer would relocate. Assuming that the above options are available, heavy land degradation in the tropics makes the influence of soil conditions and water and nutrient stresses on agricultural productivity insignificant as the basis of decisions on relocation. However, availability of these options is not guaranteed for most tropical smallholder regions. At least not in scenarios where family labour constitutes all of the human capital, farm mechanization is virtually non-existent and land is in short supply (Takane, 2008).

Second, the emphasis is on transforming the grid of land units on which each agent exists. Unless otherwise explicitly stated, the overarching land use of a particular household existing on a particular land grid is assumed to be agricultural. This means that the agricultural activities on this grid have a significant role in the overall impact on behaviour. This is hinted at in the rural migration sub-model proposed by Rajan and Shibasaki, (2000). Here the thresholds of population pressure in one area influence LUCC at another, except for the facts that (i) the agent eventually relocates to that area and (ii) the particular grid falls into any LUC category, and not just forested areas. This rural migration sub-model is sufficiently accurate to represent agents acting at a distance if it is implemented for the individual household for which socioeconomic factors would either replace or complement population pressure minus the relocation aspect.

Deadman *et al.,* (2004) describe the results from a simulation model that explored how humans understand the spatial, social, and environmental components related to LUCC, and particularly deforestation. Based on a heuristic decision-making strategy, the authors used, among others, factors such as household characteristics, burn, and soil quality, in which agent interaction was influenced by a labour pool. They contend that the effects of land-use decisions made by households affect the land cover of their plots and ultimately that of their region. It is evident how the plot's land cover was affected as the colonists accumulated wealth and labour to increase both perennial and pasture production at the expense of annuals at the individual plot level. However, linkages pointing to the latter case of deforestation in the region are not so clear, except at the commencement of colonization when a significant portion of the land was deforested. Constrained availability of household labour culminated in a stabilized perennial and annual production simulation on the one hand and decreased pasture production and, subsequently, increased mature forest on the other. The resulting simulation did not, however, reflect the observed trends, especially in pasture production (Deadman *et al.*, 2004). This could be attributed first to the implicit representation of household labour availability dynamics, in which households interacted through a local labour pool that excluded external labour demand and supply factors. Second, there is an effect of non-resilience of the model framework by which only pasture could be grown when a certain pH threshold is attained. As such, and depending on soil characteristics, many of the plots could have coincided with unfavourable conditions for pasture. This is notwithstanding the fact that, as technology progresses over time, the influence of burn and soil quality declines so much so that, in later years, such biophysical factors tend to be insignificant in decisions about land use.

In an effort to consider changes in land use in the context of a single market, Macmillan and Huang, (2008) tackled the connected problems of production and consumption decision-making and market interactions, with agricultural intelligent agents in a spatial context. The model presumes the existence of a single settlement surrounding which there is a heterogeneous landscape capable of supporting agriculture. In the tropics, however, agricultural activities are typically driven by risks and uncertainties, limited information, and, most importantly, non-profit goals (Schereinemachers and Berger, 2006). As a result, markets rarely influence what crops will be produced. Taking this into the context of deforestation of protected areas, the landscape would be considered in the same way, except that the market settlement would be replaced by the protected area. However, instead of observing land-use changes in the agricultural setting, the focus would be on monitoring how land cover (forest) in the protected area changes in connection to the production and consumption decision-making of the smallholder farming which surrounds it. This is achievable because, in contrast to the highly heterogeneous landscape in the Macmillan and Huang, (2008) model, it is established that, without economic realizations, rural smallholder communities of the tropics tend to be conspicuously less heterogeneous and decentralized (e.g., Wada *et al.,* 2007). This homogeneity in household activities tends to result in thresholds being reached even when individual changes are small and slow in nature, thereby leading to large-scale LUCCs including deforestation if the neighbourhood has a protected area. Macmillan and Huang, (2008) did propose that a production rule based on neighbourhood behaviour would be a more sensitive and representative approach. Though they did not experiment with it, it is hoped that this approach would provide valuable insights into the behaviour of complex systems such as these.

Experimenting with fluctuating rubber prices in the Kalimantan regions of Indonesia, Sulistyawati *et al.,* (2005) described a simulation model that studied the possible impacts of greater involvement of cash cropping in swidden agricultural systems. The study explicitly simulates the land-use decisions about the number, type, and location of swiddens geared toward fulfilling customary household requirements, rather than profit maximization, before tracking the economic consequences of this decision. While this effort points to a success story of modelling individual smallholder decision-making in the tropical regions, the model was based on an overstretched assumption. First, while they (Sulistyawati *et al.,* 2005) acknowledge the opening up of the communities due to development in the region, it is surprising that the modelled community was assumed to be closed to the extent that population size was entirely determined by births and deaths. Again, globally, farm labour dynamics dictate fluctuating population sizes as labour tends to be contracted from outside the community (Takane, 2008). An interesting factor, though, is the extent to which households prefer growing their own food first and engage in off-farm activities when there is no work to be done in the swiddens. Sulistyawati *et al.,* (2005) explicitly incorporated rubber tapping as an income-generating activity (IGA) depending on the household deficits. It should be mentioned here though, that, where frontier agriculture is involved, these IGAs tend to include deforestation.

2.4 Structural analysis of tropical deforestation and MAS

2.4.1 Entities of decision-making

LUCCs are largely due to deforestation, grazing land modifications, and agricultural intensification that result largely, but not exclusively, from population growth and poverty (Lambin *et al.,* 2001). Though land-use systems in rural tropical regions are characterized by a large degree of variability, most of the population is primarily engaged in smallholder agriculture. The variation generally stems from differing aspirations, attitudes, and resources among farmers (Mathews *et al.,* 2007), such that neither population nor poverty alone constitutes the major underlying cause of LUCC (Lambin *et al.,* 2001). Instead, LUCC is a collective response to economic opportunities (Lambin *et al.,* 2001). As a result, the degree of variability among individual farm units is exacerbated when factors such as markets and policies are incorporated into the models.

It is unclear how representative the assumptions of Lambin *et al.,* (2001) are for smallholder farm households in the tropics, given that these households' activities are typically driven by risks and uncertainties, limited information, and, most importantly, non-profit goals (Schereinemachers and Berger, 2006). This is in contrast to farms in temperate areas, which have more information and opportunities and an overall aim to maximize profits.

Without such economic realizations, rural smallholder communities of the tropics tend to be conspicuously less heterogeneous and decentralized (e.g., Wada *et al.,* 2007). Much of the simulated variability, however, depends on data availability. For instance, decision-making at the village level would provide the most variability in the Laotian context, but the model proposed by Wada *et al.,* (2007) used a cluster of villages to define the 'agent', owing to a lack of data at the village level. Such data limitations are important even when statistical quantification, rather than the spatial distribution, of deforestation is the main focus. Despite the fact that it was averaged across the variation of the individual agents (villages), the model of Wada *et al.,* (2007) accounted reasonably well for the spatial patterns of shifting cultivation at the village scale.

Agents in a simulation represent the individual or collection of entities that make land-use decisions. In most models, including the LUCITA model (see Deadman *et al.,* 2004), these decisions are confined to the pieces of land owned by the households. Although the uses for the individual plots within a household vary, the overarching land use of a particular household is assumed to be agricultural unless it is subdivided, as in the LUCITA model. To understand how these farm-based decisions influence deforestation and LUCC beyond the farms, it is important to explore how they extend onto adjacent forested areas. This observation prompts scrutiny of the labour requirements, social and nonmonetary influences, and land availability in the smallholder system, and how they relate to the chosen decision-making entity. The overall production of a tropical smallholder farmer household does not appear to be influenced by whether the household is primarily female or male (Takane, 2008). However, household age and size, especially when the population is predominantly young, requires further consideration.

The second dimension is to incorporate social (nonmonetary) influences on decision-making into the modelling framework (Kohler *et al.,* 2000). For example, Evans and Kelley, (2004) MAS approach incorporated education level as an important nonmonetary factor in land-use decision-making. Izquierdo *et al.,* (2003) reached similar conclusions when they explored the influence of social approval on adopting farming techniques. However, it is important that modellers should be cognizant of the fact that farmers in the developing world generally use relatively simple rules, guided by rational principles, to satisfy their needs (Simon, 1957). As in Becu *et al.,* (2003), Balmann, (1997), and Berger, (2001) focused on several hypothesized sources of inefficiency, including a lack of physical infrastructure, failing institutions, market imperfections, and limited information flows (Schereinemachers and Berger, 2006). While all these have clear policy relevance and may be addressed through policy interventions, they are external to the farmer as a decision maker. As such, these models are far from being able to identify the individual influence of the farmer's cognitive capacity as a decision maker. Worse still, in tropical regions, farm households do not perform complex algebra to make optimal decisions (Schereinemachers and Berger, 2006).

Coupled with the uncertainties of natural phenomena, and as the growing season progresses, the smallholder requirements of many households tend to be supplemented by off-farm activities. Faced with land scarcity, adaptation of the agricultural system to increase yield is an obvious alternative (Guyer, 1997). However, for a smallholder farmer in rural tropical areas, increasing commercial output is not easy, and as a result these farmers tend to seek off-farm employment (see Sulistyawati *et al.,* 2005). In doing so, the agricultural smallholder sector suffers, the agricultural system fails to adapt, and more pressure is placed on the already scarce land and forest resources.

Further explorations of the spatial patterns of land-use changes in rural tropical areas should consider the social bonds existing among the farmers. These bonds tend to guide the household activities in a relatively homogeneous way, as evidenced by the Laotian example, where individual households are strongly embedded in their local village communities (Wada *et al.,* 2007). Scheffer and Carpenter, (2003) pointed out that slow and small changes such as these can result in thresholds being crossed, leading to large-scale changes in land-use patterns. The unpredictability of such radical changes often leads to counter-intuitive outcomes (Lynam, 2002).

2.4.2 Representation of decision-making

Manson, (2001) emphasized that feedback mechanisms are important to an understanding of the deterministic nature of complex phenomena, such as deforestation. This stems from the realization that the analytical modelling approaches used so far assume a unidirectional process between driving factors and impacts. However, in reality, the influence of land-use change may alter future land use as a consequence of feedbacks (Verburg, 2006). This realization is different from the path-dependent dynamic modelling approach in which land-use change at time t_2 depends on the earlier land use at time t_1 (Manson, 2001).

Lambin *et al.*, (2003) observe that at all spatial (local, regional, or global) and temporal (direct or indirect) scales, the influence of feedback processes can be to either dampen or amplify the effects. Despite some simplifying assumptions, Verburg, (2006) presents a simulation of a combined land-use change and erosion⁄sedimentation model that dynamically linked feedbacks between land-use decisions and landscape processes. The patterns of land-use change were clearly influenced by the inclusion of feedbacks: for example, patterns of land abandonment were found in places where there was severe gully erosion (Verburg, 2006).

However, traditional research methods have not been designed for synchronous analysis at multiple scales (Overmars and Verburg, 2006). The general solution has been to structure models using either a top-down or a bottom-up approach in which aggregate regional factors constrain system changes. From that position, proximate decision makers calculate changes influenced by both local and regional conditions. Though boundaries between top-down and bottom-up approaches have been drawn, strict adherence to one or the other does not allow for explicit inclusion of feedbacks when determining the location and rate of system changes. Greene, (2000) hypothesized that simultaneous regression provides a platform to include feedbacks, as discussed by Verburg, (2006), limiting spatially explicit information to world regions or other large administrative units. Similar scenarios that consider the costs and benefits of modelling the interactions between local and region factors, using either hierarchy or feedback modelling, abound in tropical developing regions (see Deadman *et al.,* 2004, Wada *et al.,* 2007).

While most modelling approaches are aimed at assessing deforestation patterns and their associated impacts, it is noted that the decisions concerning land use are made by agents (e.g., land owners, government agencies, or other institutions). In many of these approaches, the unit of analysis is a piece of land where land-use changes are calculated in order to produce spatial maps. The disadvantage of these land-based approaches is a poor match with the agents of land-use change. It can be argued that individual farmers are not explicitly represented when the units of simulation do not match the units of decision-making (Verburg, 2006). MASs have emerged as an alternative to simple, highly abstract models, and have successfully simulated both individualistic and collective behaviour in land-use decision-making (see Evans and Kelley, 2004, Ligtenberg *et al.,* 2004, Parker and Meretsky, 2004). However, it is difficult to adequately represent agent behaviour and link it to the actual deforestation. Despite their strength in describing and exploring decision-making, MASs may inadequately represent spatial patterns of tropical deforestation due to the difficulty in representing feedbacks between agents' behaviour and forest units.

Incorporating feedback is further complicated by time dependency change factors, which can create feedback into the system, causing significant changes. In computer simulations, this time dependency directly influences the computational time and efficient use of computer resources when using MAS. Using a 10-year (1980–1990) time span, Rajan and Shibasaki, (2000) obtained satisfactory results in simulating LUCCs, just as Prasad *et al.,* (2001) did when running a 70-year (1960–2030) simulation. As discussed by Evans and Kelley, (2004), the temporal extent of a simulation relates directly to the temporal resolution at which the model runs; higher temporal resolution is achieved at the expense of the spatial resolution that can be achieved. In addition, in tropical regions, a lack of available data compounds the problem.

2.4.3 Implementation of decision-making

The preceding argument has highlighted the shortfalls in the understanding of the actual processes operating at the individual decision-making level and how the descriptive and explanatory approaches of MAS influence model results. However, the spatial context in which these entities interact is equally important. MASs must be coupled with a cellular component to represent the landscape in which individual farms are located in space and time (Parker *et al.,* 2003, Ligtenberg *et al.,* 2004, Manson, 2005). Balmann, (1997) observed that similarities between the agricultural entity of concern and CAs should be identified before such a framework is adapted to the assumptions of tropical deforestation. Balmann, (1997) identified four main characteristics of CAs: (i) they consist of a spatially discrete and regular *n*-dimensional set of identical cells; (ii) each cell can only be in a finite number of states; (iii) the states of the cells are computed simultaneously by a deterministic rule that consists of a finite number of discrete computations; and (iv) the computation rule only considers the local history of the cell and its neighbors. In land-use modelling, the cell states tend to represent particular land 'quality' interpretations, any one of which determines the activities of the particular land use (Balmann, 1997). It should be noted that spatial locations determine the types of activity in which the farm household would engage (Berger, 2001). It has been demonstrated that computer simulations combining MAS (for the individual farm/households) and CAs (for the temporal and spatial components of the landscape) provide a good insight into the individual activities that have a significant influence on deforestation trends at the macro level. It is hard to imagine that the pixel approach of CAs represents the agents of land-use decision-making (Couclelis, 2001). However, Verburg, (2006) observes that if the actual links that people have with the land are known, then direct links between the decision-making entities and the spatial entities of simulation are achievable.

There are two broad categories of the agent decision-making architecture that have been tested and widely accepted: optimizing and heuristic agents. The key difference between these is that heuristic agents have neither the information to compare all feasible alternatives nor the 'computational' power to select the optimum (Schereinemachers and Berger, 2006). Heuristic agents build on relatively simple rules of a search process guided by rational principles (Simon, 1957). Optimizing agents rely on the ability to process large amounts of information on all feasible alternatives, and always select the best one (Schereinemachers and Berger, 2006). The intuitive nature of heuristics makes them more transparent and therefore easy to validate. However, constructing a decision tree that is representative of the human thought process is not easy (Schereinemachers and Berger, 2006). The critical component in the heuristic approach is identifying not only the most important decisions but also the correct sequence in which they are taken (Schereinemachers and Berger, 2006). Furthermore, appropriate conditions (e.g., saturation levels) need to be set: for example, determining how much is 'enough' money and labour and how the decision tree is to be parameterized (Schereinemachers and Berger, 2006).

A variety of optimization approaches are available, but the most common ones include mathematical (see Balmann, 1997, Berger, 2001, Becu *et al.*, 2003) and genetic (see Manson, 2005) programming. Mathematical programming (MP) is a computerized search for a combination of decisions that yields the highest objective function value (Schereinemachers and Berger, 2006). As opposed to the heuristic approach, MP requires the explicit specification of an objective function. In LUCC and deforestation modelling, objectives of agents, which include income, food, and leisure time, tend to be similar for both MP and heuristic approaches.

While the complexity of the architectural building blocks of agents varies, consumption is most important in the tropical regions because farm households consume a substantial amount of their own crop and livestock. Consumption dynamics should therefore be considered explicitly (Schereinemachers and Berger, 2006, Cabrera *et al.*, 2010). Sadoulet and de Janvry, (1995) and

Huang and Lin, (2000) suggest that such consumption functions can be statistically estimated from household budget data, because they quantify relationships between expenditure and income, prices, and household characteristics. Most of these consumption functions, as opposed to production functions, can be specified as minimum consumption levels in relation to household size (see Deadman *et al.*, 2004, Huigen, 2004). Micro-economically, consumption and production decisions in tropical developing regions cannot be separated, because market goods cannot be fully substituted for home-produced goods. More especially when the markets are imperfect or decision-making is subject to high levels of risk (Sadoulet and de Janvry, 1995). As noted by Cabrera *et al.*, (2010), the method of decision-making alters land-use trajectories and overall landscape dynamics, but these effects may not be apparent during the design or testing of the model.

Chapter 3

Background

3.1 Study Area

Dzalanyama forest reserve is located to the south west of Malawi's capital district of Lilongwe (see Figure 3-1). It was declared a forest reserve in 1922 with some parts of it being shared and bordered by the districts of Mchinji and Dedza and the whole of its western border forming the national boundary between Malawi and Mozambique (Munthali and Murayama, 2011). It is some 60km from the capital's city centre and lies between latitudes 14.18° and 14.61° S and longitudes 33.35° and 33.92° E. Sitting on a range of hills bearing the same name, Dzalanyama forest reserve covers approximately 935 km^2 of land. And while the local name Dzalanyama means "full of wild animals" the story is different lately due to poaching. Game life in the reserve has deteriorated such that as of present only monkeys, rabbits, and deer exists though it still boasts of a vast variety of natural forest cover with a little exotic breeds introduced on its commercial plantations (Government of Malawi, 2006). Biophysically, the reserve overlooks the Lilongwe plains and it rises between 1100 to 1659m above sea level (see Figure 3-1 and 3-3).

Situated in the capital district the study area is easily accessible. Availability and the ease with which both primary and secondary data for the activities could be sourced made modelling deforestation of the reserve attainable. It also represents a typical case of the dynamic and complex relationship among the activities of the smallholder agriculture-based rural communities in Malawi, the urban socio-political influences and sustainable management of natural resources. While the activities may be specific to the study area, the basic interactions and subsequent impacts are endemic to most protected areas in Malawi. As such, choice of the study area will serve to address not only deforestation of Dzalanyama but also act as a template in other forest reserves.

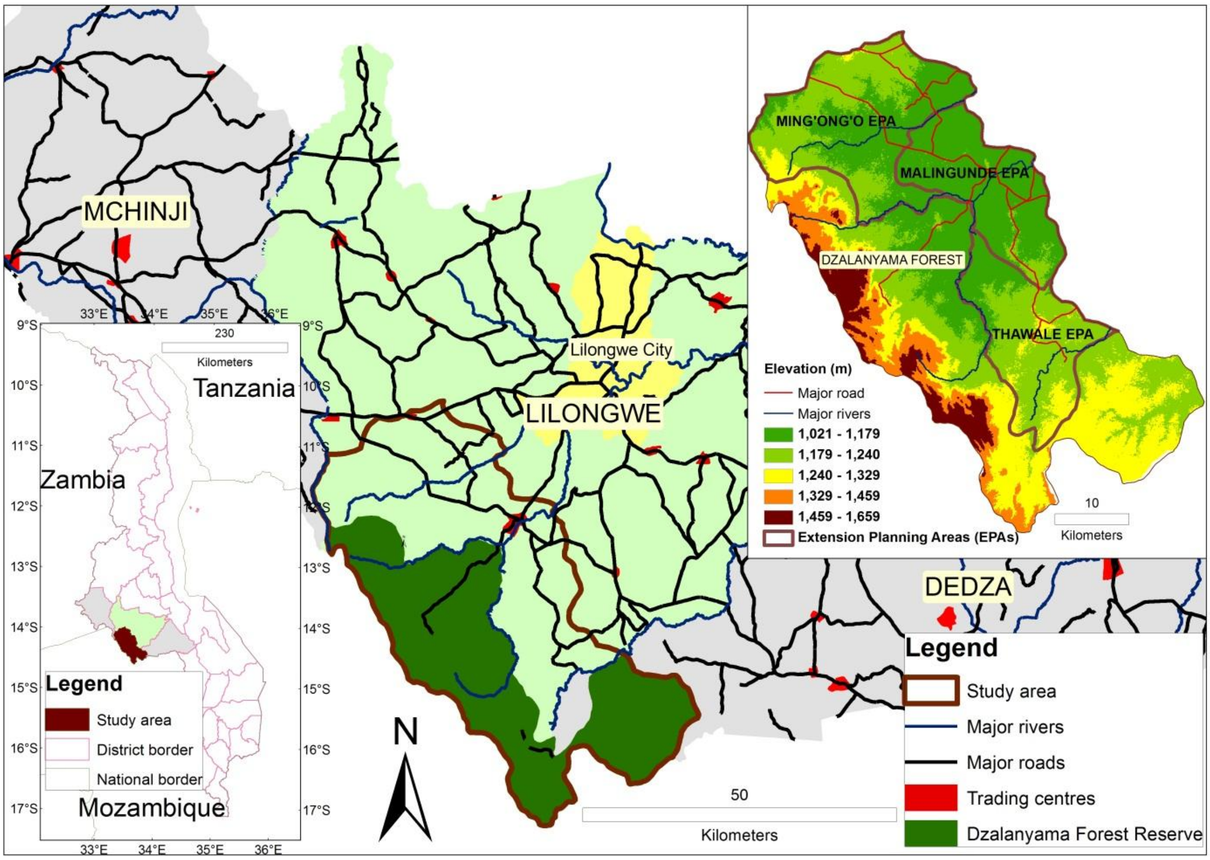

Figure 3-1: Study area

There are several stakeholders involved with the welfare of Dzalanyama Forest reserve including the Department of Forestry (DoF) falling under the Ministry of Lands, Natural Resources and the Environment of the Malawi Government. However, my focus will be on the agricultural activities and operations involved in the areas immediately surrounding the reserve for reasons I will explain shortly. There are five Extension Planning Areas (EPAs) that directly border the forest reserve, namely: Ming'ong'o, Malingunde, Thawale, Chafumbwa and Msitu (see Figure 3-1). An EPA is an agricultural administrative unit that implements central government agricultural policies through provision of good farming methods to households on a one-on-one visitation basis (extension services). An extension service is the transfer of knowledge from researchers to farmers carried out by extension workers (EWs). EWs are therefore, mandated to advise farmers on their decision-making and stimulate desirable agricultural developments by providing informal education to farmers through meetings, demonstrations and field days. As such EWs require necessary orientation and facilities in technical knowledge, farming skills, economic analysis, research procedures and communication abilities. Under the Ministry of Agriculture all the named EPAs fall in one Agricultural Development Division (ADD) which is Lilongwe except for Msitu that falls under Kasungu ADD. All the agricultural technical details trickle through the ADD, which means Msitu has a separate technical line of command from the rest of the EPAs.

On the other hand, due to decentralisation, all the administrative activities are done at district assembly level, through the Local Government ministry. This means the first three of the named EPAs fall under the same District Assembly, Lilongwe, while Chafumbwa EPA belongs to Dedza Town Assembly and Msitu EPA belongs to Mchinji Town Assembly (see Figures 3-1). The study area falls in Traditional Authorities Masula and Masumbankhunda where the Chewa people are the dominant ethnic group and trace their ancestral roots to the first Bantu-speaking 'Maravi' who migrated into Malawi some Two thousand years ago (Bryceson 2006). Chichewa is the common language in the area and both matrilineal and patrilineal cultural marriage systems are in existence. The organizational structure at district level and how the ADDs fit into the picture is shown in Figure 3-2 followed by a picture depicting some graphical representation of the study area (Figure 3-3).

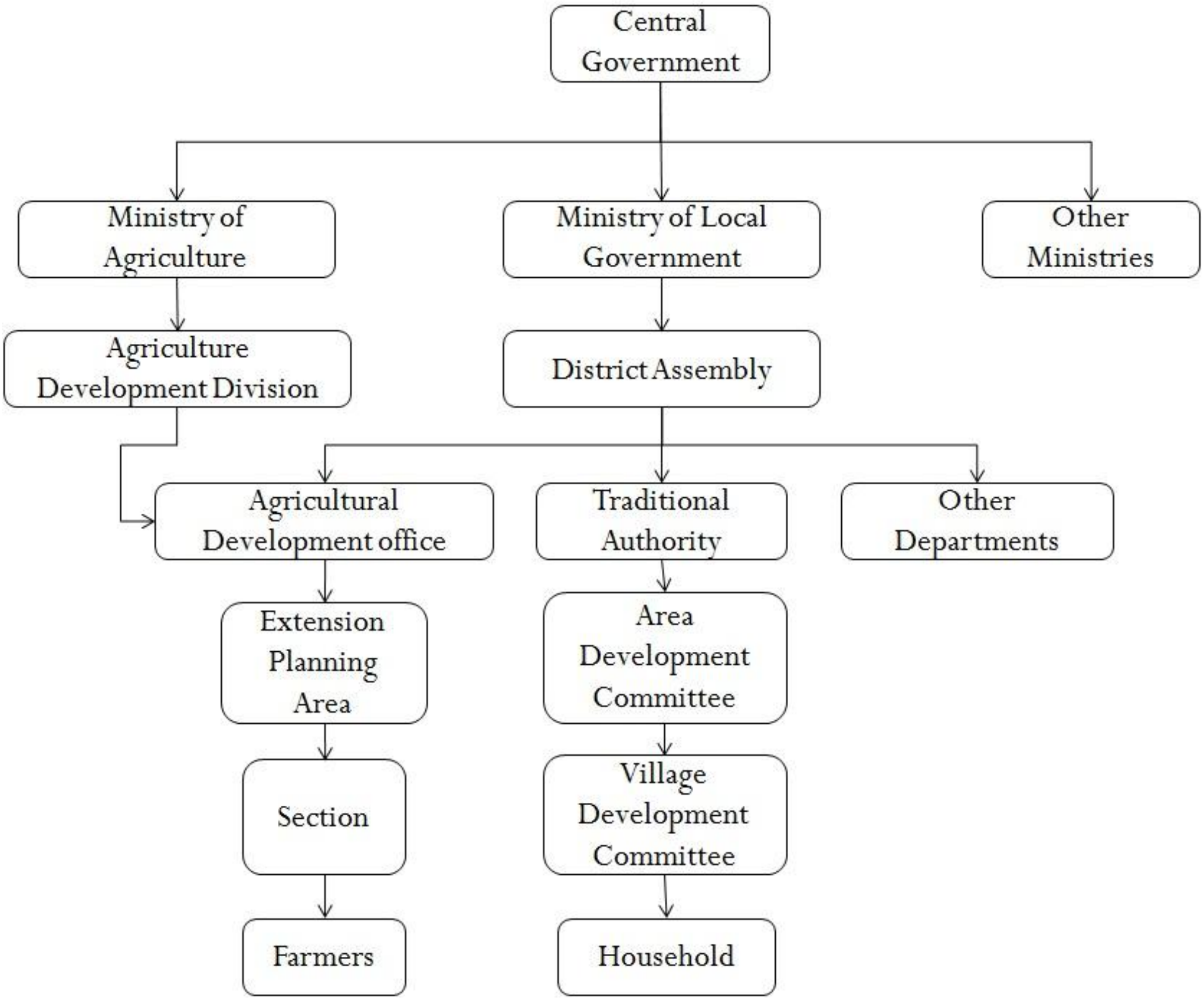

Figure 3-2: District/Town Assembly organizational structure

Figure 3-3: The top images show a typical village setup (left) and a hoe-prepared farm plot (right). The bottom images are a view of Dzalanyama hills (left) and a stream flow with Brachystegias (Miombo) trees on its banks in the forest reserve

While the technical and administrative overlap gets sorted, I chose to focus on Ming'ong'o, Malingunde and Thawale EPAs for the reasons that: a) they all belong to the same district assembly and ADD which is Lilongwe; b) they cover the longest combined border stretch with the forest reserve (see Figure 3-1); and c) because of reason (a) above data collection for the modelling process was not only cheap but also easy to trace with Lilongwe being the capital district of Malawi. The average land holding size is as shown in Table 3-1 for the three chosen EPAs. In Table 3-2, a short summary of the field household data collected in 2011 and 2012 is presented. It is evident that a substantial majority of the total arable land is under smallholder farming system and there is almost no mechanization. Again, the decline in total arable land per household is noticeable where it averages just below a hectare in 2012 from slightly over a hectare around 2006.

Table 3-1: Average land holding size for Thawale, Ming'ong'o and Malingunde EPAs

EPA	Total Farm Families	Total Smallholder Arable land (ha)	Average land Holding size (ha)	Sections*	Extension workers**	Extension services Ratio***
Thawale	18,665	25,000	1.34	8	5 (16)	1:3733 (1:1167)
Ming'ong'o	22,667	30,766	1.36	15	12 (30)	1:1889 (1:756)
Malingunde	18,282	19,667	1.08	12	9 (24)	1:2031 (1:761)

** See Figure 3-3*
***Number of extension workers as of 2011 (recommended)*
****Extension worker-to-farm family ratio as of 2011 (recommended)*

(Source: Government of Malawi, 2006 and Malasa D., personal communication, 14 April 2011)

Table 3-2: Descriptive summary statistics of field survey data collected (land is in hectares)

Household characteristic	Minimum	Maximum	Mean	Std. Deviation
Household size (incl. children)	1	12	4.39	1.72
Children less than 15years	0	9	2.12	1.36
Children older than 15	0	8	0.49	0.89
Total arable land	0.20	7.69	0.97	0.55
Land allocated to Maize	0.00	4.45	0.59	0.32
Land allocated to Ground nuts	0.00	2.43	0.32	0.25
Land allocated to Tobacco	0.00	1.21	0.015	0.08
Land allocated to Soya Bean	0.00	0.81	0.022	0.07
Land allocated to Cassava	0.00	0.40	0.002	0.02
Land allocated to Sweet potato	0.00	0.81	0.020	0.072
Land allocated to other crops	0.00	0.40	0.003	0.024

3.1.1 Field survey

To understand the household activities further, a field survey was conducted in April 2011 and January 2012 where 3,533 households were interviewed. The households were selected from 12 sections of Malingunde EPA with each section contributing at least 290 random households. The following socio-economic data were collected: household size; total land under cultivation; total land under maize (corn) cultivation; land under other crops; annual total maize yield (food); access to production materials (hybrid seed and organic fertilizers); estimated annual income; access to good farming methods; IGAs that the households engage in apart from cultivating their land; labour and land availability; soil condition; and educational level of the head of household.

Most of the households have four or more members (Table 3-2), and illiteracy levels are very high with most respondents unable to read or write. All households depended on family labour to produce crops on the pieces of land, which most of them claimed were sufficient for their production provided all production resources were available. Almost all households grow maize as a staple food in conjunction with varying combinations of cash crops that include ground nuts, sweet potatoes, soybeans, tobacco, and cassava. 74 % of those interviewed could not produce enough food for their households during the past couple of years due to lack of access to: 1) production materials (cash unavailability); 2) subsidized production materials from central government; and 3) good farming methods (extension services). 64 % of those that failed to produce enough food engaged in off-farm non-agricultural activities to supplement food requirements for their households.

The mean household size of the data collected is 4.4 persons (Table 3-2), requiring 792 kg of maize to feed itself per year (Malasa D., personal communication, 14 April 2011). The land that the households allocated to food production averaged 0.59 ha. According to production estimates of the 2010 growing season this hectarage can produce at best 2,700 kg of maize provided there is availability of production materials and at worst only 500 kg (Malasa D., personal communication, 14 April 2011). With most households lacking crop production materials it is not surprising that most of the households failed and continues to fail to produce enough food to sustain their households. The average total land per household (0.97 ha) is higher than the average allocated to food production (0.59 ha). One would, therefore, expect an adjustment in the crop distribution to allocate more land to food production. However, the field survey revealed that the crop combinations rarely change at the end of the cropping year. As such, despite having room to expand the land allocated to food production to compensate for the low production due to lack of materials, the households continue to disadvantage themselves year in, year out. The poor crop markets do not help to rescue the households as the cash crops cannot fetch enough to cover the food and cash deficits.

3.2 Smallholder farming in Malawi: the challenges

It is evident that agriculture determines the pace and direction of overall economic growth for Malawi. Operating under low-input rain-fed system the country's economic performance thus depends largely on how its smallholder farmers perform (Tchale, 2009). Malawi's agricultural productivity, particularly among the majority of the smallholder farmers, has however fallen a long way below its potential given the available technology. For example, local maize and Burley tobacco yields have rarely reached 1.5 tonnes per hectare (Tchale, 2009). This is substantiated by the 74 % of the respondents who could not produce enough food in the field survey.

However enhancing agricultural productivity is very difficult for most farming households where vast numbers of the households live in exceptionally high-risk environments in which basic survival is a day-to-day uncertainty. Commercial maize production has become increasingly unremunerative for smallholder farmers, other than those producing on a large scale with adequate capital to buy fertilisers (Levy *et al.*, 2004). Farming households are failing to achieve their households' basic food security from their small plots (Bryceson, 2006). As of

2002 the per capita maize production was on average 49 kg for the ultra-poor, 63 kg for the poor and 116 kg for the non-poor, all falling short of the average 155 kg minimum staple food requirement, and leaving even the non-poor in a deficit position (World Food Program, 2002; Government of Malawi, 2007b).

Mvula *et al.,* (2003) identifies three main rural categories based on household level of food deficiency: the 'well-to-do' who have food stocks that on average last eight to nine months of the year, the ‘a bit well-to-do' who have food sufficient to cover four to six months, and finally the ‘have-nots’ who usually have less than one hectare of land and harvest only one to two months of their household’s food supply needs (Bryceson, 2006; Mvula et al., 3003). While everyone’s food security has deteriorated, the latter group have experienced the most precipitous slide downwards (Bryceson, 2006). A detailed survey by Peters, (2006) found that the poorest households were reducing the proportion of their maize harvest that they sold to conserve household food stocks. However, their extremely low level of food output necessitated the purchase of maize in rural markets where the government-owned Agricultural Development and Marketing Corporation’s (ADMARC) role as a price stabiliser is/was declining making them more vulnerable.

Malawi’s agricultural productivity is therefore under threat. The 2008 Population Census estimated the country’s population at 13.1 million and growing at 2.8 % per annum, possibly doubling by 2025 (Government of Malawi, 2008). This puts enormous pressure on agriculture to grow at levels sufficient to feed the growing population. I discuss the dynamics of the factors that would enhance agricultural production in the name of availability of sufficient labour, land and agricultural production materials and how they together intertwine to exacerbate the food security problems for smallholder households in rural Malawi.

3.2.1 Labour

Households' reliance on casual labour has grown so much resulting largely from the fact that the households' livelihood strategies revolve around the need to obtain food on a day-by-day basis. Labour is, therefore, a key asset for smallholder households in rural Malawi. The quality and quantity of labour available to the household in terms of numbers, educational level, skills, and health constitute the human capital. This, then, becomes the basis for constructing household livelihood strategies (Takane, 2008) that are essential in enhancing the agricultural productivity. *Ganyu* is a short duration casual labour contract for unskilled work paid in cash or kind (Takane 2008; Whiteside 2000). It, according to Bryceson, (2006) and Takane, (2008), comes in forms that include: *kontalakiti* (contract), seasonal labour performed on a nearby or far more distant farm; casual *ganyu* labour on the commercial estates, especially the tobacco estates; *ganyu* labour to alleviate famine distress involving agricultural or non-agricultural work; and *ganyu* labour performed by children for their own or parents' economic benefit.

As population grew, labour supply began to outstrip demand reducing the bargaining power of *ganyu* workers with respect to wage levels and the nature of work tasks demanded. The growing prevalence of HIV/AIDS compounded by occasional famine reinforced this tendency by limiting the number of people who were able to employ *ganyu* labour (Bryceson, 2006). The removal of the fertiliser subsidy in the early 1990s, when Malawi government ceded to World Bank pressure, caused smallholder farmers to drastically reduce their improved input usage. This caused maize productivity to decline and shift smallholder allocation of labour from their family farms to larger farms producing at scale, or to non-agricultural activities (Bryceson, 2006). As a consequence of the sub-optimal labour inputs, productivity on smallholdings further decreased (Edriss *et al.*, 2004).

Still more *Ganyu* labour remains important in rural Malawi for two main reasons: i) it provides supplementary labour to labour deficient households, due to HIV/AIDs related issues that has led to high numbers of female/children headed households; and ii) it provides a ready sustainable way of obtaining food when households' food supplies ran out. It interrelates with the high risks in agricultural production and the problem of food deficit, and provides a means for risk sharing for the employers and food security for the labourers (Takane, 2008). To the majority of the rural households, therefore, *ganyu* labour has become a way of life, but one that exacerbates rather than solves the household’s food production constraints (Bryceson, 2006). This is the case because both opportunities and necessity of *ganyu* increase during the rainy season. The opportunities arise from the increased agricultural activities as the cropping season begins. It becomes a necessity because this is the time in which most households are worst hit by food deficiency after depleting their food reserves. The overall effect during this season is labour allocation dilemma for *ganyu* labourers. Trying to satisfy their immediate need for food, they are forced by circumstances to do *ganyu* labour at the critical time when they should be preparing, planting and weeding their own fields (Bryceson, 2006). In doing so, they are likely to exacerbate their future food deficiency. Being a rain fed agricultural production system, planting late has serious consequences on output. Even then, poor households do not have much of a choice but plant late because they must first do *ganyu* to earn enough cash to buy production materials. Some employers allow their labourers to work on their own fields in a timely fashion. However, this benevolence is counteracted by the rising population dependent on *ganyu* for an increasing portion of their livelihood, which is becoming an entrenched feature of many local rural economies in Malawi.

There is a widening gulf between the shrinking number in rural Malawi who can afford to hire *ganyu* labour and the expanding number who sought *ganyu* labour so much so that *Ganyu* has been an integral part of deepening rural impoverishment over the past 15 years (Bryceson, 2006). Most *ganyu* labour is performed by smallholders for other smallholders with most villages having at least one better-off farmer who hires *ganyu*: hiring between 2 to 20 labourers often for two to three times a week for several months (Pearce *et al.,* 1996). Meanwhile the terms of *ganyu* contracts have been worsening with Edriss *et al.*, (2004) and Takane, (2008) reporting that real wages have declined significantly in the past couple of decades.

In terms of gender, Takane, (2008) reports that female-headed households are more likely to engage in agricultural wage labour (*ganyu*) than male-headed households. However, though women are just as equally involved in *ganyu* as men, there are large gender differentials in remuneration. Men reportedly tend to earn twice as much as women of the daily piecework rates (Whiteside, 1998). These differentials are locally justified in that: i) men put in a full day's work whereas women are distracted by domestic duties; ii) besides attitudinal differences regarding the value of female labour, there is the very real issue of need for cash from women. And with their lack of other income sources, women's opportunity costs of their labour are significantly lowered; and iii) women are restricted to *ganyu* work close to their homes whereas men venture into farther distances thereby increasing their chances of finding higher wage levels (Bryceson, 2006; Chipande, 1987). These factors lead female-headed households into a vicious cycle in that maize production per hectare, for instance, for female headed households tends to be low due to low fertiliser use (lack of cash to buy) compared to the male headed households. As a result this low maize production forces the female headed households to seek other means of income which are in essence non-existent making them go back to the low paying *ganyu*. In addition and for similar reasons female headed households tend to avoid growing labour-intensive cash crops such as tobacco which would fetch more income for the livelihoods of the households (Takane, 2008).

Traditionally women and youth work as unpaid family labour in household agricultural production. Much in the way that their husbands expect them to work unpaid on the family farm, now women expect their children to do *ganyu* labour to contribute to household income (Bryceson, 2006). This expectation from the mothers is not strange as traditionally children have always helped with the household workload doing domestic labour, cultivating the family agricultural fields as well as doing household-based crafts like weaving and rope-making without expecting any remuneration. As such women see their off springs as economic dependants who should be helping them to earn *ganyu* income, rather than doing *ganyu* on their own account. However, as Bryceson, (2006) notes teenage estrangement is thwarting this traditional ideal of a collective rural smallholder household labour effort with modern youth increasingly unwilling to do so. She attributes this trend of events to the introduction of free primary education in the mid-1990s. Though it was an extremely positive development, the free primary education tends to serve as a communication barrier between the younger children generation and parent generation. This is largely because with the free primary education the rural youth are already better educated than their parents. On top of that there is the issue of human rights that came with the introduction of multiparty democracy in 1992. At village level, many older people equate human rights with the perceived individualistic behaviour of the youth at the expense of age-old moral values of the collective community (Bryceson, 2006). This literary revelation is made worse when you consider that the field survey for the study area showed that 60 % of the total population for the 3533 households surveyed is comprised of children of which 81 % are aged 15 or below. However, only 30 % of the households are female-headed.

In this context where farm mechanization is virtually non-existent all farm work is done manually. As such having access to necessary labour for agricultural production, therefore, directly affects the levels of household farm income. This is the case in that in addition to working on a household’s own farm, labour may also be deployed in off-farm economic activities, thus providing additional income to the household (Takane, 2008).

3.2.2 Land

The importance of family labour in farm work and the lack of mechanization in agricultural production imply that the availability of family labour is a prerequisite for a household to increase farm size. However, the increase in farm size using abundant family labour is possible only under the condition that land is readily available for the expansion of a family's farm. This is not always the case in most of rural Malawi today, because increasing population pressure on the land has considerably reduced the scope of farm expansion onto uncultivated land (Takane, 2008).

Like other countries in sub-Saharan Africa, Malawi's soils have been depleted of essential nutrients as a result of increased pressure on land and insufficient inputs (Tchale, 2009). A study conducted by Smaling in 1998 indicated that Malawi's soils lose on average 40.0, 6.6 and 32.2 kg per hectare per year of nitrogen (N), phosphorus (P) and potassium (K), respectively. Apart from declining soil fertility, Malawi's land holding sizes, especially in the smallholder sector, are also declining. As shown in Tables 3-1 and 3-2, the average total arable land per farm household reduced by at least 0.1ha between 2006 and 2012. According to the Malawi Poverty and Vulnerability Assessment report (Government of Malawi, 2007b), over 90 % of the total agricultural value-added comes from about 1.8 million smallholders who own, on average, less than 1.0 ha of land. Land pressure is particularly intense in the southern region of Malawi where the per capita average landholding size can be as low as 0.1 ha, whereas the average per capita landholding size in the other regions is 0.2 ha and more (Tchale, 2009).

3.2.3 Other resources

Generally land and labour availability are limiting factors to agricultural production for most households in Malawi. It is evident from the literature and field survey that land is a scarce resource in the study area (see Table 3-1 and 3-2). Minus the factors discussed in section 3.2.1 and 3.2.2, the yield stagnation and fluctuations can, therefore, be attributed to factors such as low adoption and less intensive use of productive agricultural technologies, unreliable rainfall, production inefficiencies (lack of production materials) and poor soils.

Most households surveyed in the study area expressed satisfaction with the amount of land, family labour they have, and the condition of their soils for agricultural purposes. 74 % of the households surveyed that could not produce enough listed lack of access to production materials, no access to farm input subsidy program (FISP) from central government, and lack of good and modern farming techniques. The former two directly relate to the overdependence on the declining economic returns from *Ganyu* labour as per the highlighted issues in section 3.2.1 above while the latter relates to inadequate capacity by the agricultural ministry to educate the smallholder households on new farming techniques. This is especially in the form of under-staffing of EPAs. For instance, Malingunde EPA has twelve sections with each section supposed to have at least 2 extension workers. However, as of January 2012 each of these 12 sections only has one extension worker putting the ratio of extension worker-to-farm household at 1:1488 instead of at least 1:744. Apart from the issue of under-staffing these EPAs are also heavily under-funded limiting further their potential to reach out to more smallholder households (Malasa D., personal communication, 14 April 2011). On top of that, these extension workers often lack the necessary orientation and facilities in technical knowledge, farming skills, economic analysis, research procedures and communication abilities (Mobarak *et al.*, 2012).

3.3 Charcoal production in Malawi

As established in section 3.2 above, the smallholder agriculture sector is struggling to sustain the households' subsistence requirements. Households are then being forced to seek off-farm non-agricultural economic activities to supplement their requirements. Many of the IGAs that are environmentally sustainable require substantial capital injections. This makes them out of reach for most of the rural households forcing them to resort to engaging in environmentally unsustainable activities. In the study area these activities include brick burning, firewood collection, tobacco curing and charcoal production. The common and environmentally detrimental to the forest reserve is charcoal production (see Figure 3-4). Heavily dependent on forest resources, these activities have negatively affected the operations of neighbouring Dzalanyama Forest leading to its massive deforestation in the past couple of decades.

Figure 3-4: Top-left: charcoal selling market in the outskirts of Lilongwe city; Top-right: A standard bag of charcoal (roughly 40Kg); Bottom: Two villagers transporting charcoal and fuel wood to the market using bicycles.

The charcoal industry provides significant employment throughout its value chain. Out of the approximately 100,000 people that owe their lives to charcoal, slightly over half of these are involved in the actual production. 62 % of the producers are in the small- (less than 30 bags (see Figure 3-4) per month) to medium-scale (between 30 – 100 bags per month) production ranges together producing approximately 67 % of the annual charcoal tonnage (Kambewa *et al.*, 2007). The small-scale producers' category is comprised of those venturing into charcoal production as a coping mechanism against food shortage and/or cash needs while the medium-scale ones are slightly business-oriented but are not well cash-endowed (Kambewa *et al.*, 2007). It follows therefore that there is a big overlap between the smallholder farming households, who struggle to feed themselves and in food deficit year in year out, and the small- and medium-scale charcoal producers.

While the agricultural production challenges pushes the smallholder household into tighter corners to survive, the nearby urban city of Lilongwe provides an opportunity in the study area. It is estimated that 90 % of the urban families in Malawi rely on biomass energy. Charcoal is the dominant energy source for the main urban centres of Blantyre, Lilongwe, Zomba and Mzuzu (Government of Malawi, 1998). Many of these urban families cannot manage without charcoal as a source of energy making urban consumption the primary market for this highly traded commodity. In fact less than 30 % of the urban population is connected to the national electricity grid (Kambewa *et al.*, 2007). This implies that more than two-thirds of the urban households have no choice other than to use biomass fuels as their primary energy source. Located in close proximity of Lilongwe city and directly linked with relatively accessible unpaved road (see Figure 3-1), charcoal from Dzalanyama forest reserve has a ready and steady market (Figure 3-4).

Charcoal is produced by heating fuelwood (or any other raw biomass) in some type of kiln with limited access to air in a process called carbonization (Pennise *et al.*, 2001). Carbonization creates a fuel of higher quality than the original fuelwood. Besides charcoal, fuelwood is the main energy carrier for cooking and heating in the developing world. According to Emrich, (1985), charcoal production can be categorised into traditional and modern. The traditional approach (Figure 3-5) is characterised by:

- zero or low investment;
- use of construction materials which are at hand on the site or available nearby, e.g. clay, soft-burnt bricks;
- zero or low maintenance costs achieved by avoiding metal parts in the kiln construction as much as possible;
- manpower not being a major concern; normal raw materials consisting largely of wood logs (other types of biomass may be carbonised also);
- by-product recovery being limited owing to the fact that no sophisticated equipment is employed; and
- typically being a family or cooperative initiative.

A marked difference between traditional and modern charcoal production is the employment of sophisticated technologies and/or high capital investments in which case returns from the process include some other essential by-products of the carbonization process. Again because of the inherent inefficiencies in the traditional approach, there is also a substantial loss of carbon and energy from the starting fuelwood (primarily as carbon dioxide) and, a significant production of products of incomplete combustion (Pennise *et al*., 2001) than in the modern approach. Much of the charcoal produced today has been made by families or small businesses using the traditional approach. Though inefficient, as it employs simple technology and low capital investment, the traditional approach is nevertheless precise and skilful (Emrich, 1985).

Common in Malawi among the traditional approaches of charcoal production are the pit and earthmound kiln methods (Figure 3-5). To cut on raw material transportation costs, small- to medium-scale charcoal makers produce their char at the place where they collect the raw materials. Because this will involve frequent movements as the raw materials on the place get depleted, employment of heavy equipment is reduced to bare minimum if not none at all (Emrich, 1985). The business of charcoal making requires skill, patience and readiness to observe correct working methods at all times and in all weathers. These "technical secrets" are usually handed down from father to son and kept under wraps and well-guarded by the family (Emrich, 1985). An important part of the charcoal-making experience concerns the insulation of the charcoal pit or earth-mound to control air flow. If not well controlled, excess oxygen will cause the charcoal to burn away to ashes and destroy the result of several days' work not to mention wasting the fuelwood. Depending on the amount of wood and the size of the kiln, the charcoal making process can take more than a month, although the smallest kilns will produce charcoal in a few days (Kambewa *et al.*, 2007). The insulation material readily and cheaply available is earth and it is one of the factors that greatly contribute to the inefficiencies of the traditional approach.

Figure 3-5: Earthmound (top) and pit (bottom) traditional kilns under construction

As earlier indicated the traditional earth mound or pit kiln technology is known to be wasteful and inefficient with local studies placing the efficiency ratio at little more than 20 % (Makungwa, 1997 and Openshaw, 1997). Coupled with increased urban demands for charcoal, as the urban population grows, there are marked land cover transitions near production sites, usually concentrated along roads and around villages. However, these land cover transitions in Malawi are not caused by total charcoal supply being out of balance with wood stocks. They are rather usually due to failures to provide incentives to manage wood production in a manner that allows regeneration in and around charcoal producing areas (Kambewa *et al*., 2007).

Charcoal demand and production peaks during the rainy season (Kambewa *et al.,* 2007). This is again the critical time at which the rain fed agriculture needs close attention especially in terms of labour. It's during this very season that households are worst hit by food scarcity after depleting their food reserves. As such, as discussed in section 3.2 this competition for labour between the households' own farm plots and the need to survive the season spirals the household food security deeper into deficit. As the smallholder farming households surrounding Dzalanyama forest reserve continue to be in perennial food deficit, the forest resources seem to offer an easier way out of perpetual poverty. Being readily accessible from/to the urban centre of Lilongwe city, the plight of Dzalanyama Forest Reserve is dealt a further blow to sustain the biomass energy demands of the rapidly increasing population of the capital. Not surprising then, Dzalanyama Forest Reserve is one of the most threatened natural ecological systems in Malawi due deforestation caused largely by charcoal production.

Chapter 4

Assessing deforestation trends of Dzalanyama forest

Understanding the dynamics of LUCC has been fundamental in rural land management especially for sustainable agriculture and forestry management in sub-Saharan Africa (Kamusoko *et al.,* 2009). This stems from the fact that the majority of the population living in rural areas of central and southern Africa depend on smallholder agriculture and other natural resources for their day-to-day needs (Campbell *et al.,* 2000; Gambiza *et al.,* 2000). Endowed with vast natural resources essential for its socioeconomic development, the region's sustainable development efforts continue to be obscured by the escalating deforestation and soil degradation rates due to population growth and poverty among many other factors (Kamusoko *et al.,* 2009). Not spared of this predicament is Dzalanyama Forest Reserve, which is one of the most threatened natural ecological systems in Malawi. It is understood, generally that the degradation resulting from these human pressures is exceeding the regenerative capacity of the forest reserve (Munthali and Murayama, 2011). While it is imperative to employ tools that support the understanding of the causes and consequences of land use dynamics, the objective of this chapter is to present a scenario analysis that will quantify and highlight the near-past, current and near-future deforestation of Dzalanyama forest reserve. I do this to draw awareness on the gravity of the deforestation situation and hence push for concerted efforts to reverse the current trends. The sub-chapters 4.1 present the data sources and the methodology used. I then present and discuss the results in sub-chapters 4.2.

4.1 Data sources and methods

Thematic Mapper (TM) remote sensing imagery from USGS's Landsat for the years 1990, 2000 and 2010 were used. For 1990 the imageries were observed on July 11, 1990 and May 12, 1989 while 2000 were observed on August 31 and July 21, 2000. For 2010 the imagery was observed on May 6, 2010. The Landsat images consist of spectral bands 1 to 7 and have a ground resolution of 30m. These images were selected for the study as they provided suitable cloud-free (<30 %) spatial coverage and relatively high spatial and spectral resolutions. Each of the Landsat imagery bands can provide unique information for the interpretation of surface features. For example, Band 1 provides information about the penetration of water bodies, and thus is able to differentiate soil and rock from vegetation and detect cultural features. Band 2 is sensitive to differences in water turbidity. This band can separate vegetation types, e.g. forest and cropland from soil. In this band, settlements and infrastructures have a brighter tone, while vegetation has a darker tone. Band 3 is a spectral region of strong chlorophyll absorption, and therefore it can distinguish between vegetation and soil. It is capable of separating primary forest, secondary forest and cropland areas. Band 4 can distinguish vegetation and its conditions and is therefore able to separate primary from secondary forest (degraded forest). Water bodies are a strong absorber of near infrared energy, and therefore this band clearly delineates water bodies and separates dry and moist soils. Band 5 is capable of separating forest, cropland and water bodies, as forest has a darker tone than cropland, while water bodies have an even darker tone than forest or cropland. Band 7 has the capacity to separate secondary forest from primary forest areas. Aside from the visualization of individual bands, composite images are also employed to enhance the interpretability of features of the images (Khoi and Munthali, 2012).

Due to sensor inherent data acquisition inaccuracies and also data handling, preparation and processing errors, ground reference data in image analysis is very important (Thapa and Murayama, 2009). Therefore aerial photographs for accuracy assessment purposes were acquired for selected parts in the study area from Malawi Government's Department of Survey. Because of poor record keeping, August 1986 aerial photographs were the closest I could find as reference data for 1990 and due to lack of resources the department does not have aerial photographs for the later years after 1995. So for the 2000 image I used aerial photographs observed in June and July of 1995. Google Earth's GeoEye 2010 aerial photograph was used as reference data for 2010.

4.1.1 Hybrid supervised classification

Satellite images contain information in digital numbers, and therefore a classification procedure is required to transform these digital numbers into understandable geographic features. This is known as information extraction. An image processing procedure can be defined as a process of extracting distinct geographic features or categories from satellite images based on supervised or unsupervised classification methods. The unsupervised method is the division of the whole image into different categories based on the similarity of spectral signatures, where each category is labelled with a specific name corresponding to a particular geographic feature (Khoi and Munthali, 2012).

Supervised classification, on the other hand, is based on prior knowledge of the study area to classify the images into geographic feature patterns. The process of supervised classification may follow several steps summarized into two stages. The first stage is the identification of categories of real-world features, i.e. LUC types, using the prior knowledge of features in a study area from both primary and secondary data. This step is known as the delineation or identification of training areas. The second stage is the labelling of classified categories using a selected classification rule (Khoi and Munthali, 2012).

Anderson *et al.*, (1976) noted that frameworks for organizing and categorizing information extractable from a remotely sensed image should be determined from classes that are not only important to the study but also discernible from the present data. Visual interpretability of the acquired Landsat images was enhanced using contrast stretch and true colour composites (Bands: 4, 3 and 2 for Red, Green and Blue respectively) together with aerial photographs for selected areas.

Unsupervised classification (Leica Geosystems, 2005) was used to initially categorize all the pixels in the images into a manageable number of 50 classes. Spectrally similar classes were then merged and labelled accordingly to prepare training areas to be used to define spectral signatures for five final classes (water, forest, cultivation/settlement, grass/wet/bareland and plantation). The class Grass/wet/bareland was chosen for conventional purposes as the current land use literature for the area has grassland and not wetland or bareland as a category (Government of Malawi, 2006) despite the areas being wet bare soils generally following streams with a mixture of grass.

The supervised classification rule used was Maximum likelihood classifier. It assumes a special probability distribution, for instance a Gaussian distribution, of the given data a priori, and then determines the appropriate parameters from the training data (Keuchel *et al.*, 2003). Each data pixel is then assigned to the class for which its values are most likely, i.e. the class with the highest a posteriori probability (Swain and Davis, 1978). The maximum likelihood algorithm is commonly employed in the separation of LUC classes. This method is useful because it requires a minimum of training area data while achieving high accuracy (Khoi and Munthali, 2012). The maximum likelihood classifier is a probability density function that is associated with a particular training area signature. The classifier evaluates the probability that a given pixel belongs to a particular category, and then classifies the pixel to the category with the highest probability. The image interpreter trains the software to recognize spectral values associated with the training areas. After the signatures for each land use/cover have been defined, the software uses those signatures to classify the remaining pixels (Khoi and Munthali, 2012).

Spatial correctness in image classification analyses is very important such that accuracy of the thematic maps produced is often compared in remote sensing studies (Thapa and Murayama, 2009). Accuracy assessment therefore, compares the predicted (i.e. classification) results to geographically referenced data that are assumed to be true (Lillesand *et al.,* 2008; Richards and Jia, 1999). This is achieved through a subjective assessment of the observed difference in accuracy undertaken in a statistically rigorous fashion. A set of 100 reference pixels, 20 from each of the 5 categories, was used selected randomly to reduce possibility of bias. Among the several measures of accuracy assessment I used the kappa coefficient. The Kappa coefficient expresses the proportionate reduction in error generated by the classification procedure by accounting for all the elements of the confusion matrix excluding all agreements that occur by chance thereby providing a more rigorous statistical assessment of the classification (Congalton, 1991). Figure 4-1 summarizes the classification and analysis procedure.

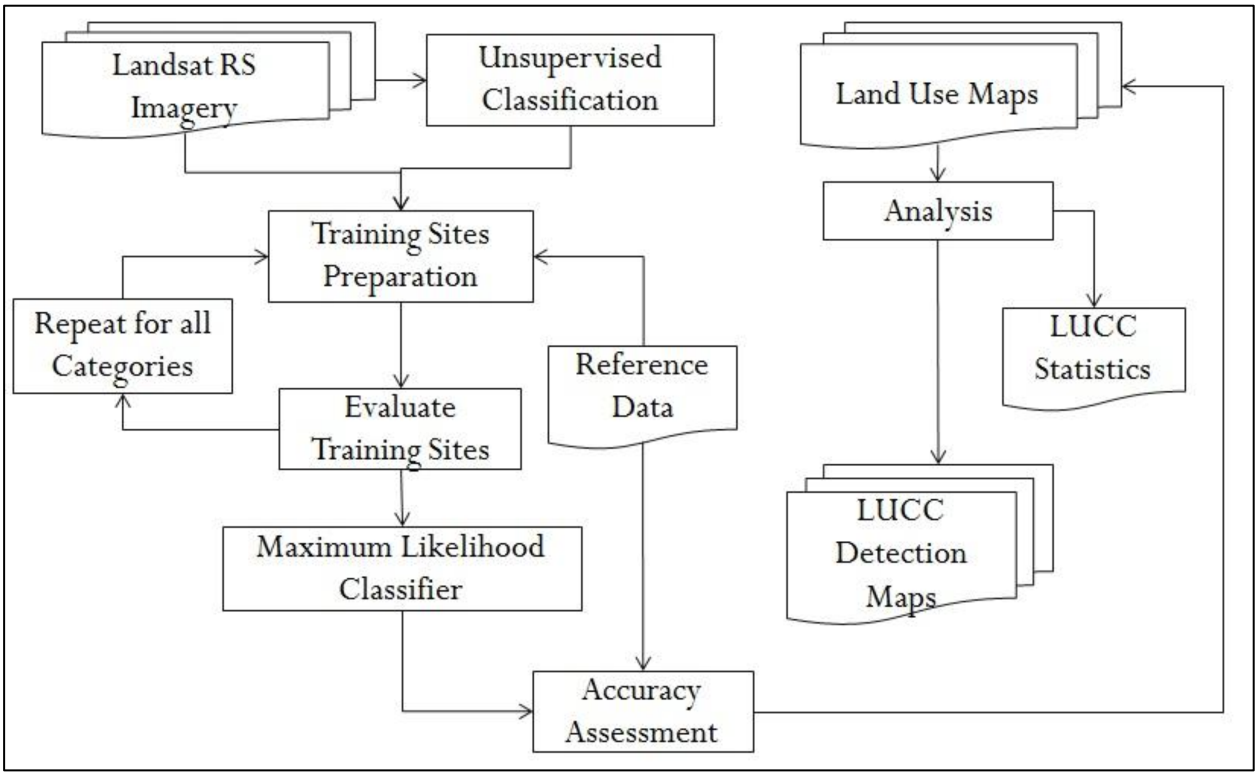

Figure 4-1: Multispectral hybrid classification combining supervised and unsupervised approaches

4.1.2 Change detection and Markov chain analysis

To achieve the overall objective of painting the picture of the present deforestation scenario and its progression in the near-past, present and near-future cases I employed change detection and Markov chain analysis techniques. While the change detection quantified and spatially located the changes from the past to present, Markov chains only quantified the changes without spatially locating where the changes will occur in future. The spatial change detection used the combine tool in ESRI's ArcGIS 10 between the 1990 – 2000 and 2000 – 2010 time periods.

Markov chain analysis is a stochastic process for which for a particular system of interest there is a set of discrete states. In the case of LUCC the states correspond to the class categories for which a particular parcel of land can belong to at a particular instance (Munthali and Murayama, 2011). The parcel of land can only be in one state at a given time moving successively from one state to the other with a probability which depends only on the current state and not the previous states (Bell and Hinojosa, 1977). The probability of moving from one state to the other is called a transition probability which can be represented in a transition probability matrix whose elements are non-negative and the row elements sum up to 1 (Briassoulis, 2000). For this case of an area subdivided into a number of cells each of which can be occupied by a given type of land use at a given time, the transition probabilities were computed on the basis of classification data between time periods which show the probability that a cell will change from one land use type to another within the same particular period in the future (Briassoulis, 2000).

4.2 Results and discussion

The dominant land uses, following the classification, are cultivation/settlement, forest and the Grass/wet/bareland. However in 2010 the situation has changed with Grass/wet/bareland and forest being in almost equal coverage. Figure 4-2 shows the forest cover scenarios for 1990, 2000, 2010 with overall classification accuracies of 80, 81, and 84 % respectively. The proportion of classification error for 1990 and 2000 was much higher due to in part the disparities in observation time of the imagery and reference data which had 4 and 5-year gaps respectively. The forest cover as of 1990 was 65,775 hectares, of which 22,031 hectares were lost by the year 2010.

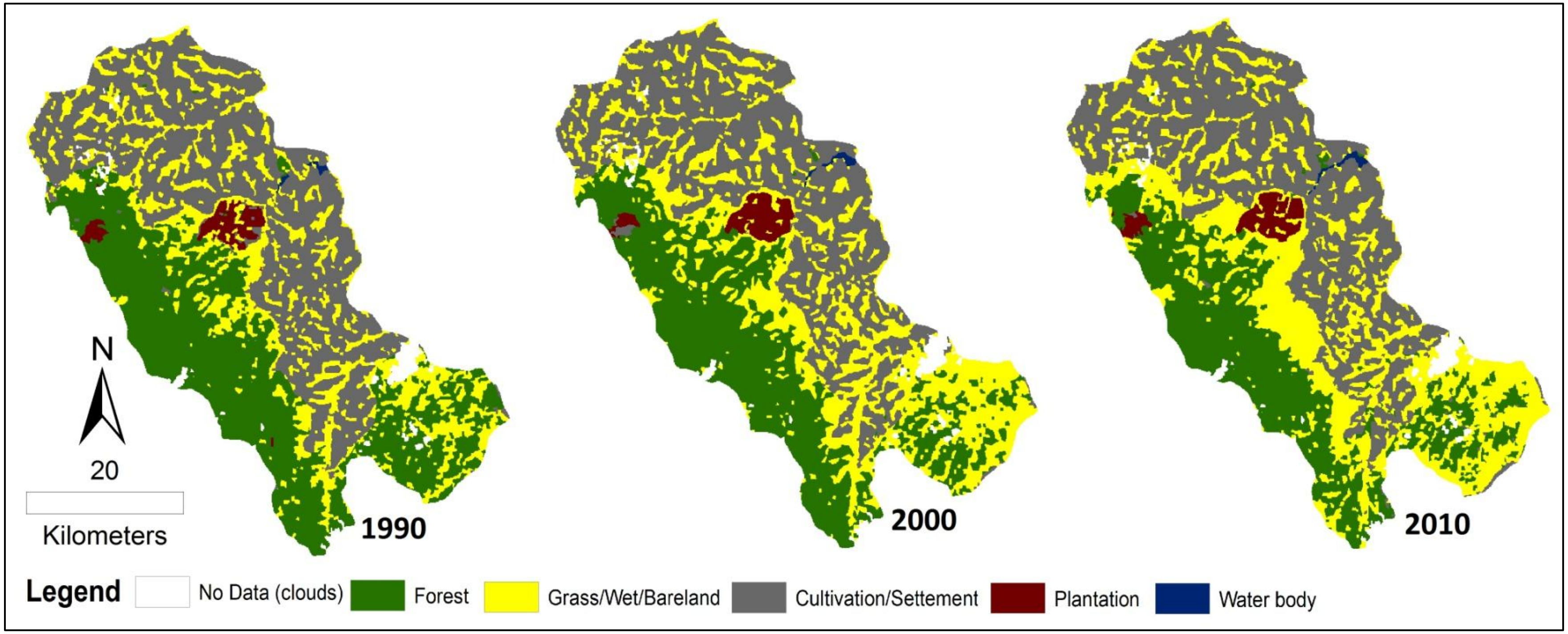

Figure 4-2: Observed land use/cover classification

Despite environmental management measures being taken by the surrounding communities, the overall land cover change results show a staggering 22,031 hectares (see Table 4-1) of forest loss between 1990 and 2010, for which the changes are equally distributed between the time intervals. Table 4-1 summarizes the land cover conversion dynamics in hectares and Figure 4-3 shows the changes spatially. In Table 4-1, each row value represents the number of hectares lost from that land cover type to any one of the column land cover types. These land cover changes suggest a dynamic population behaviour in which case the reported increased poverty levels and urban sprawl start to explain the situation for the 1990 to 2000 and 2000 to 2010 periods respectively. The economic opportunities of urban sprawl triggered collective responses such that in the typical smallholder communities a wide selection of nutritive requirements for household survival were taken directly from the forested environments than in the limited-scope smallholder agricultural activities. This underlines a situation of deforestation that is worsening in the area.

Table 4-1: Land use change between time intervals in hectares

1990 - 2000	Forest	Grass/wet/ Bareland	Cultivation/ Settlement	Plantation	Water	**Total**
Forest	0	13,029	446	160	4	13,639
Grass/wet/Bareland	3,278	0	5,784	562	81	9,705
Cultivation/Settlement	151	10,302	0	411	93	10,957
Plantation	82	241	244	0	0	567
Water	0	24	27	0	0	51
2000 - 2010						
Forest	0	13,307	293	112	0	13,712
Grass/wet/Bareland	4,808	0	7,596	228	71	12,703
Cultivation/Settlement	251	4,704	0	273	55	5,283
Plantation	23	469	38	0	0	530
Water	8	33	19	0	0	60

Note: Overall forest cover loss 1990 - 2010 is 22,031 hectares

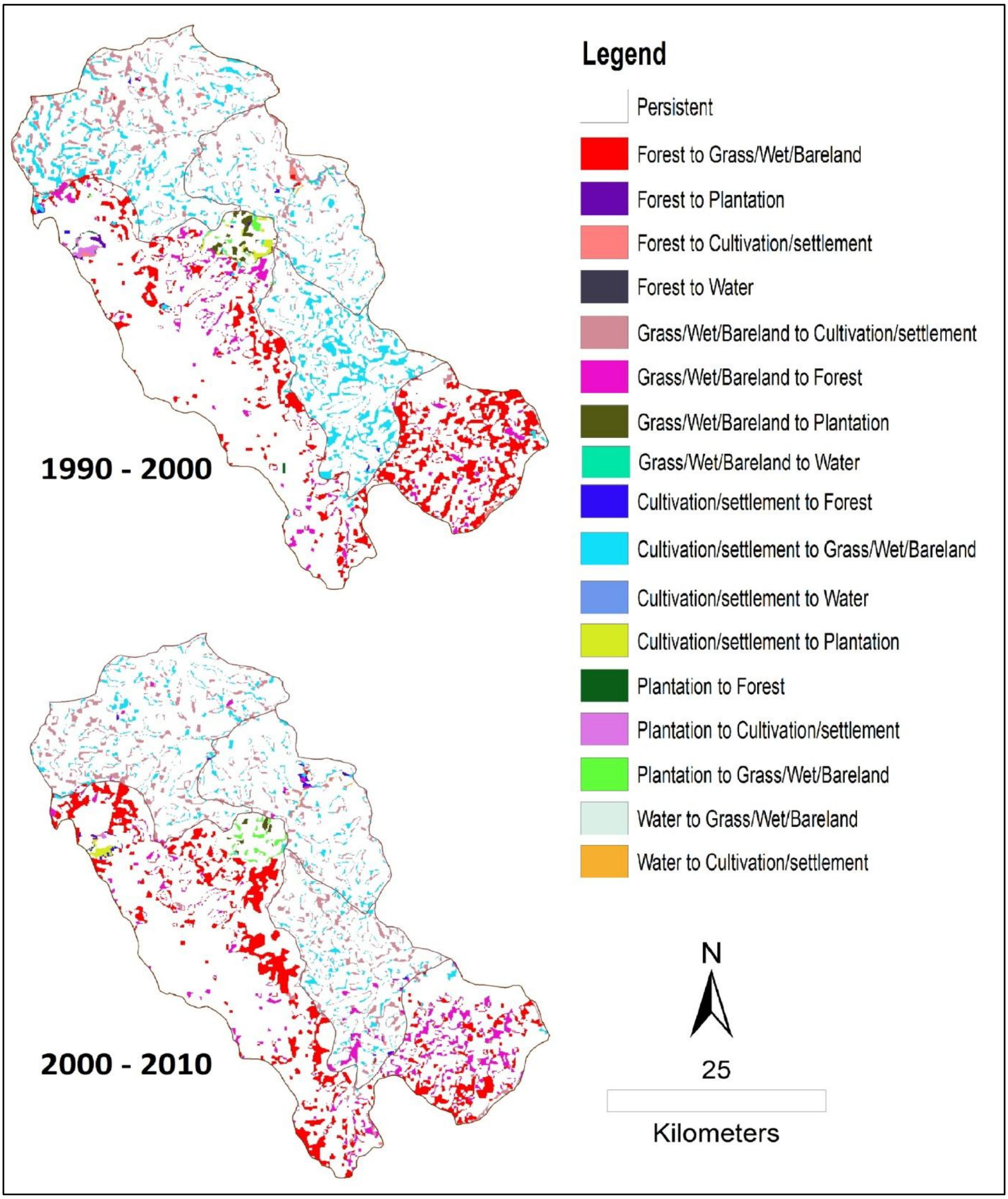

Figure 4-3: Observed land use/cover change

To ascertain the situation in the near-future I employed a Markov chain model. Here the I assumed land use change from time 1990 to 2000 and then 2000 to 2010 is a Markov chain with stationary transition probability. Each of the five land use categories was assumed to be a possible state at any given time of the chain. A Markov chain equation ($p_{ij} \times \boldsymbol{v}_j = \boldsymbol{v}_{j+1}$) was used. p_{ij} is the transition probability of state i changing to state j and $\boldsymbol{v}_j$ represent a vector of land use state j at time t_1 and $\boldsymbol{v}_{j+1}$ is the projection of land use properties at time t_2. In this study, land use change was projected for the years 2010, 2020 and 2030 by computing first, second and third order Markov chains.

Using water, forest, Grass/wet/bareland, plantation and cultivation/settlement categories as states in the Markov chain model, a transition matrix was computed and land use change statistics for 2010, 2020 and 2030 were predicted. Plantation and water are almost constant while forest continuously reduces. Compared to observed satellite imagery for 2010, the 2010 Markov chain prediction does under predict forest loss. The analysis has shown 26 % of the study area to have been forested in 2010 and to be reduced to 24 % and 22 % in 2020 and 2030 respectively. In terms of quantities, the 2010 to 2030 Markov chain trend represent 8,463 hectares of forest loss. Compared to the observed forest losses between 1990 to 2000 and 2000 to 2010 (Table 4-1), the Markov chains under predict the forest land cover changes given that the business as usual scenario triggering the changes is assumed to be maintained. Figure 4-4 shows the Markov chain predictions and a projection to 2020 and 2030 graphically. It is evident that the forest reserve is under heavy threat and the trends show no signs of abating in the near future.

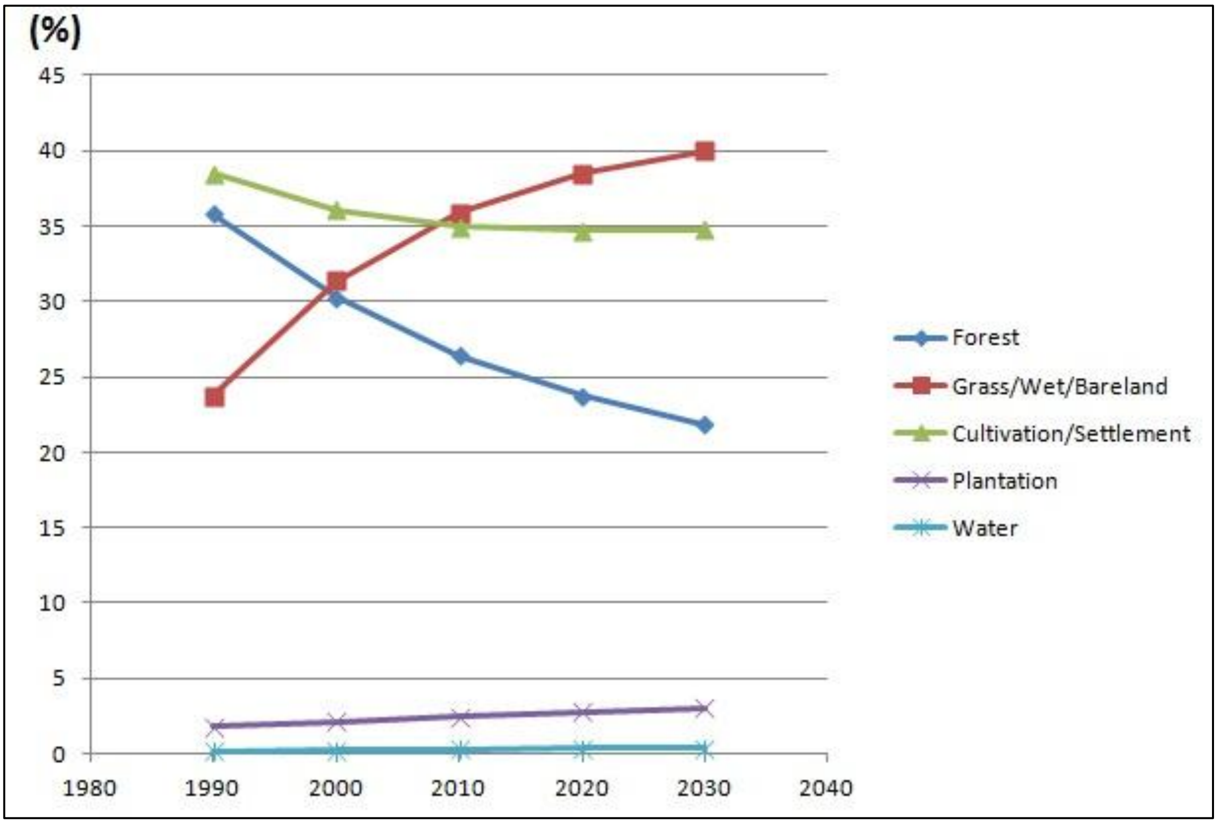

Figure 4-4: Markov chain analysis: projected land use percentages 2020 and 2030

The Markov chains analysis's predictions in this study do suffice in indicating that the situation of deforestation in the forest reserve will not abate in the near future. The under-predictions in this study are understood in the context of the memory-lessness nature of the Makov Chain model. That is, the Markov chains analysis assumed a maintained business as usual scenario in as far as the drivers of change were concerned. However, the factors causing the land cover changes evolved, for instance the intensification of commercial charcoal burning leading to massive deforestation between the years 2002 to 2005 (Government of Malawi, 2006). This is notwithstanding the fact that I grossly assumed that the observed land cover changes are stationary Markov processes. Testing these assumptions is very difficult (see Bell, 1974; Briassoulis, 2000; Clark, 1965; and Sklar and Constanza, 1991) as such I did not prove and therefore I could not guarantee the stationarity of the processes. I understand too that in our attempt to substantiate the degrading conditions of the forest reserve in the near future, I did not include constraints on possible transitions or other constraints like availability of land and other resources. This is because the focus was to pick out on the possible quantities of change regardless of whether they can actually occur or not.

The foregoing analysis highlights two related issues facing the forest reserve. First is that indeed the forest reserve is under heavy ecological threat of extinction and secondly, there is indeed dynamism in the factors driving this degradation. While not denying the role of population growth and poverty, the trend established in this study cannot be pinned down to these two factors only especially in this area where shifting cultivation is not practiced nor is there presence of any known large scale transmigration to settlement schemes and/or plantations. Despite Markov chains' failure to depict underlying factors influencing the land cover changes, a cross examination of the results against the reports that between 2002 to 2005 deforestation intensified (Government of Malawi, 2006) suggests changing economic opportunities to be one of the main driving forces. This period coincides with socio-political change in 2004 that saw a change of government policy to relocate all central government personnel to the capital city with the aim of cutting central government expenses. This created demand for infrastructural materials especially bricks and wood for extra housing for the city dwellers and charcoal and firewood for those pushed into the city peripherals. It is difficult indeed to expect stationarity in transition probabilities when such complex dynamic factors are dragged into the picture (Lambin *et al.,* 2000), however, the not-too-long 40-year period in this study made the requisite Markov chains assumptions practically achievable as supported by (Weng, 2002). Overall, the relative ease with which I inferred understanding of the dynamic driving factors from the multi-temporal land cover data surpassed the limitations the Markov chain analysis posed for the purposes of this analysis.

Indeed for a forest reserve to be losing its forest cover at such rates is very worrisome. As such the direction and magnitudes of the deforestation trends established in this study demand a rigorous approach that should incorporate the behavioural dynamics of the population living in the surrounding community including the social, political and infrastructural changes to achieve positive results. Being a largely smallholder farming based community (Government of Malawi, 2006), a model that will invoke and build on the activities at the individual farm household levels would be the most appropriate to reverse the trends and provide sustainable solutions.

Chapter 5

Simulating farm-based decision-making and deforestation in Dzalanyama: a multi-agent approach

5.1 Introduction

With advancements in remote sensing technologies there has been a proliferation of modeling tools that analyze deforestation in a spatially explicit context. However, very few of these models incorporate household analytical data sets and explicit spatial variables like land use; distance to road, river, and markets; plot sizes; and spatial household socio-economic data. Such model's outputs need to include not only estimates of the magnitude of forest clearing and degradation but also predictions regarding its location (Kaimowitz and Angelsen, 1998; Munthali and Murayama, 2012). Of these tools, spatially referenced MASs or agent based simulations appear to show particular promise for exploring interactions between human-coupled environmental systems over time. In recent years their application in the study of LUCC has grown considerably (Deadman *et al.,* 2004; Parker *et al.,* 2003). With many viewing tropical deforestation as an irreversible process leading to permanent land cover change, I describe a preliminary effort to develop a geo-computational MAS model called Dzalanyama Multi-Agent Simulation (D-MAS) to simulate deforestation of a tropical forest reserve, Dzalanyama, in Lilongwe, Malawi.

While the physical environment strongly influences where tropical deforestation occurs, Kaimowitz and Angelsen, (1998) listed several other parameters that influence agents of deforestation's decision-making regarding deforesting. These include agricultural markets, input and timber prices; wages and off-farm employment; technological changes in agriculture; and accessibility, among other factors. From these, it is evident that tropical deforestation hinges strongly on agricultural activities which could be pinned down further to the underlying population growth and its inherent pressures on land and poverty (Kaimowitz and Angelsen, 1998).

While the study simulates future LUCC (up to 2030) for the Dzalanyama forest reserve area, the objective of D-MAS is to provide a socio-scientific basis for potential policy intervention scenarios towards sustainable management efforts of the forest reserve. This chapter describes the development of D-MAS to simulate the selections of cropping decisions and a competing labour practice (charcoal production) by smallholder farmers surrounding the forest reserve. The study simulates the smallholder crop production dynamics of the individual households in the surrounding area of the reserve. It is then hoped that this understanding of the social system inefficiencies will provide insights into the interrelationships between the household socio-economic structure and sustenance of the forests reserve.

This chapter is an effort to, therefore, not only dynamically make estimates of the influences of the farm-based decision-making of the smallholder farmers on deforestation of Dzalanyama forest reserve at present and in the future, but also predict future outcomes of some particular forest resource management actions and policies. The study area was chosen because it has a wide range of biophysical and socioeconomic characteristics dominated by smallholder subsistence farming. It typifies the rural landscape in most parts of Malawi. I will use the terms "farming household" and "household", and also "smallholder farming", "subsistence farming" and "smallholder subsistence farming" interchangeably throughout the chapter unless otherwise explicitly stated.

5.2 Data sources

The primary data sourced to replicate the household farming activities is as described in section 3.2.1 from the field survey conducted in April 2011 and January 2012. The secondary data sourced includes an observed land use base map for the starting year 1990 and observed land use maps for 2000 and 2010 used is the model calibration and validation (Figure 4-2). Biophysical spatial driving factors were forest/settlement edge distance map (derived from 1990 land use base map) and distance to road and river (Figure 5-1). The road and river data sets were obtained from the Department of Forestry and UNICEF offices in Malawi respectively. Land cover change literature indicates that one of the major contributing factors to deforestation is accessibility, which is usually measured by distance from a road and from the edge of the forest itself (Kamusoko *et al.*, 2009). I included distance from river because an analysis of the observed deforestation trends showed a positive correlation between deforested areas and proximity to rivers (see Figure 5-11). It is also included because the earthmound traditional kiln approach used to produce charcoal in the area uses earth molded into mounds for insulation (see Figure 3-5). This molding is a process that requires plenty and readily available water.

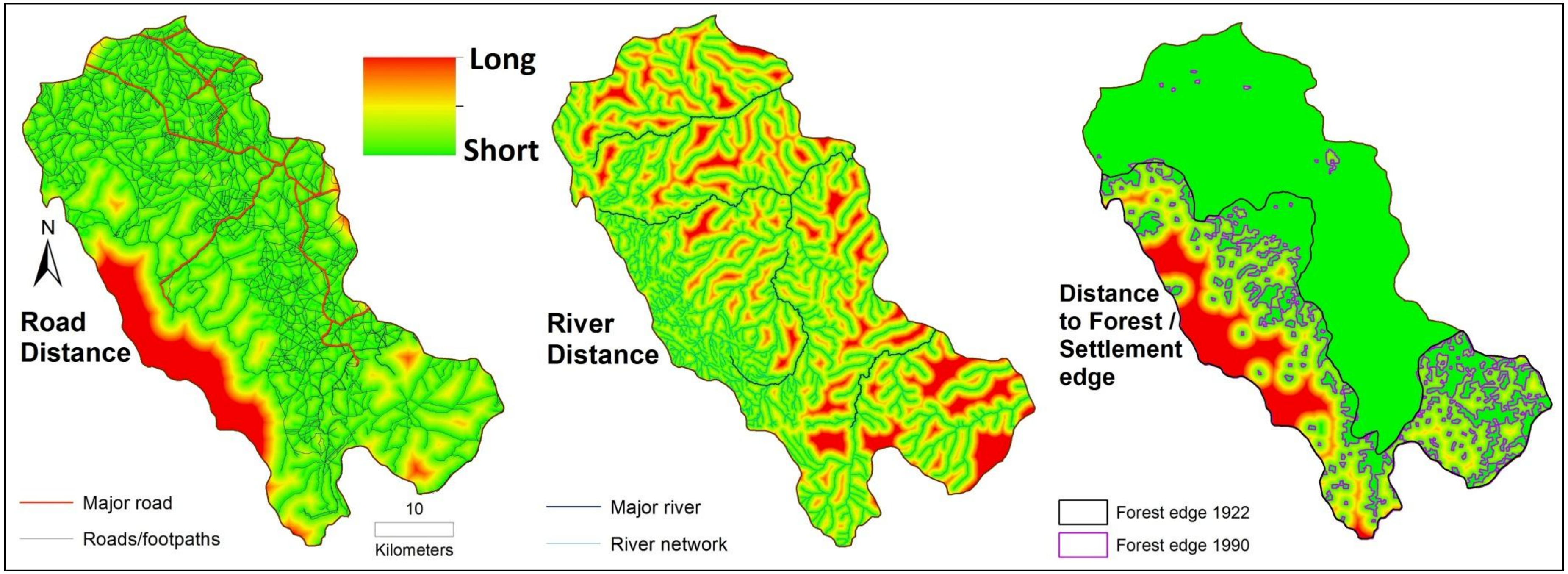

Figure 5-1: Biophysical distance factors (road, river and forest edge)

5.3 Methodology

D-MAS is an abstract representation of the forest reserve landscape, the smallholder farming households, and the processes and entities that link them. It is a spatially referenced simulation that is wholly written in Java with the Repast Simphony 2.0 toolkit (Repast, 2012). The description of the methodology follows the ODD (Overview, Design concepts, and Details) protocol for describing individual- and agent-based models (Grimm *et al.*, 2006; Grimm *et al.*, 2010).

5.3.1 Overview

There is an allocation dilemma between selection of cropping decisions and competing labour practices (charcoal production) being faced by smallholder farmers in the study area. D-MAS, therefore, hypothesizes that the smallholder agriculture crop production theories being implemented by the households in the communities surrounding Dzalanyama forest reserve combined with the biophysical attributes of the study area are impacting on the overall deforestation trends of the forest reserve itself. To test this hypothesis three entities (Figure 5-2) were developed:

i) the extension worker (EW) agent (Figure 5-3), represents a government agricultural expert tasked with the duty to impart new and better farming techniques to the farming households in a particular section of an EPA (see Figure 3-3) to improve production. The number of EWs is equal to the number of sections in the three EPAs and each EW can belong to and visit farmers in one and only one section; and

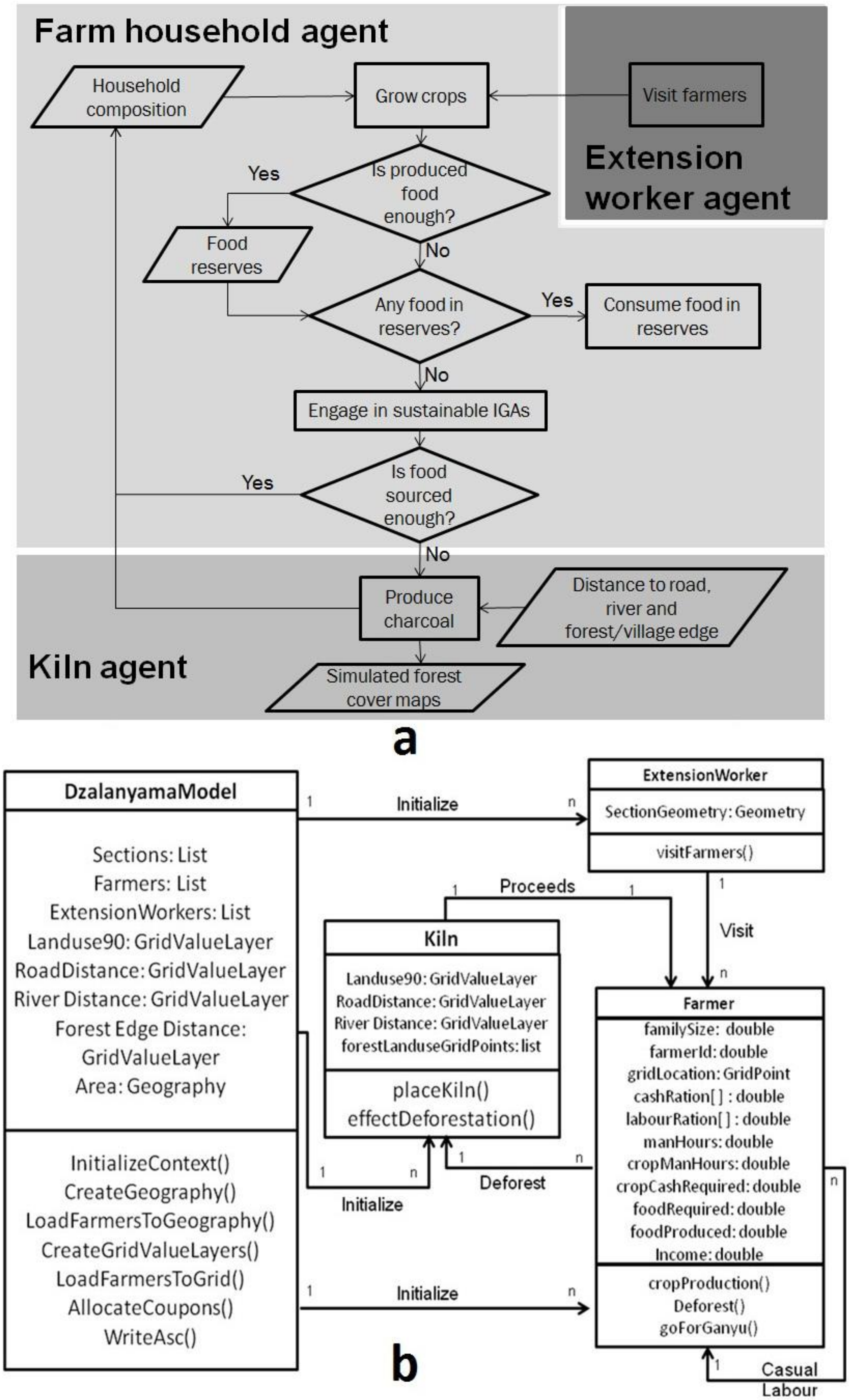

Figure 5-2: Framework of the interactions and interrelationships of the entities farm, extension worker and kiln agent. a) Flowchart; and b) UML diagram

ii) Farm household agent (FHA). These are immobile agents that represent the smallholder farming households. FHA is characterized by static attributes of family size; types of crops grown and size of each plot (acres) and number of children (separated into those above 15 and below and/or 15 years) from the field survey data. It also includes total household labour (in manhours) derived from the number of family members with children less or equal to 15 years contributing half the equivalent of a single adult. While we assumed labour to be sufficient for the household, this labour estimate is necessary for the household to be able to engage in *ganyu* labour and IGAs.

State variables for FHA include "subsidised inputs?", "enough cash for agriculture?" and "extension services?". These are boolean variables set to true if the household is a recipient of the subsidised production materials, has enough cash (earned from *ganyu*, cash crops and/or IGAs) to buy production materials, and has been visited by an extension worker respectively. *Ganyu* is engaged when a well-off household signals that it requires extra labour. For simplicity, this signal can only be perceived by farmers within a buffer radial distance of 1000 metres from the specific household that seeks to hire. This does not only bring computational sanity but also enforces a sense of realism in that *ganyu* labour is generally prioritised within close neighbourhoods. The FISP is a policy of the Malawi government to subsidize production materials for selected poorest households among the poor households re-introduced in 2004 after being stopped in the early 1990s. The household then tries to grow the crops (Figure 5-4) and engages in off-farm activities (casual labour, and other small scale businesses). The last state variable "deforest?" is also boolean and is set to true if the combined food produced and sourced from the off-farm activities still does not meet the household food requirements. At this point, the kiln agent is then engaged;

iii) The kiln agent (Figure 5-5). The FHA has been simulated as immobile. However, to produce charcoal farmers/producers need to move into the forest area. A kin is the physical location in the forest where charcoal is produced and in the simulation it is an equivalent of single grid cell (100x100m = 1ha). The kiln agent has, therefore, been abstractly represented as a resource to be used in interactions with the FHA. There can be at most 30 active kilns per time step. Because the number of FHAs is large, to reduce computation overheads, it’s the kiln agent that is simulated as mobile instead of the FHA. It responds to demands by households to produce charcoal and eventually effects the deforestation of the forest reserve. A kiln agent will move once its forest stock has been depleted on the current location. The frequency of movement and where it moves to is an emergent outcome. The frequency is determined by the need for the FHA to deforest while its next spatial location is determined by the biophysical factors (Figures 5-5 and 5-6).

The length of a time step represents a year and the simulation runs for 40 time steps representing 40 years beginning 1990. For the biophysical factors and land use base map, a grid cell represents 1 ha (100 x 100m) and the model landscape spans 615 × 676 hectares. The process overview and scheduling of the simulation is as shown in the pseudo code below executed once per time step.

Allocate subsidized farm inputs to households

Extension worker visits households

If Extension worker is within 200 m

Household receives extension services

End if

If another household is seeking casual labourers and is within 1000 m

If this household has some extra labour available

Household goes for casual labour

End if

End if

Household produces/grows crops

If there is a food and/or cash deficit

Kiln agent deforests to produce charcoal

End if

Update system-level results

5.3.2 Design concepts

The key emergent outcome is the frequency of the kiln agent movement which represents the frequency of deforestation. The kiln agent frequency to move emerges largely from how the households perform in crop production which determines the frequency of them requesting to deforest to cover food deficits. The households' adaptive behaviour is to deforest when their objective - to produce enough food from growing crops - is not met. Due to the low literacy levels, I assume limited learning for the households. For instance, if a household is visited by an extension worker this year and is taught new methods of growing crops, it will be able to boost its production for that year. However, it is not expected to reproduce these farming techniques the following year unless an extension worker visits it again. For similar reasons, the households are again assumed not able to estimate long term future consequences of their decisions.

Interaction in the simulation is in three categories: household-to-household in the case of *ganyu* labour provision, extension worker-to-household in the dissemination of good farming methods, and household-to-kiln to effect deforestation (see Figure 5-2). All interactions are local and in each category one agent intentionally signals in order to induce the interaction and the other perceives the signal. While it was important to model the actual causes of variability and hence emergence, some processes are assumed to be partly random to ensure that model events, for instance deforestation, occur within some specified realistic frequency. For model validation, the percentage of households that are food deficient at every time step will be observed. The frequency with which the kiln agent moves and where it moves to will also be tracked.

5.3.3 Simulation details

The initial state of the model is such that all farm household agents are loaded from an ESRI shapefile whose attributes define the static attributes of each agent. The shapefile attributes are replicated from the 3,533 farming households' characteristics to cover all the households in the study area (59,614 households; see Table 3-1). The number of households and their attributes is the same in every simulation run, except for cash income, which is set randomly between 9,000 and 30,000 Malawi Kwacha (MWK) or US$36 and 120 for each household (Government of Malawi, 2005). The number of extension workers (representing infiltration of good farming methods), the selling price of charcoal, and the number of recipients of the farm input subsidy can be varied at the beginning of every simulation run.

The extension service was implemented as shown in Figure 5-3. The red star represents a randomly visiting government extension worker mandated to train the farmers new and better farming techniques. The visits are random to account for issues of under-staffing and under-funding. And for computational simplicity, instead of simulating a visit to each individual household, a farmer is deemed to have been trained in new farming methods if s/he is within 200m of the visiting extension worker in that particular simulation year for that particular visit.

FISP targets the poorest of poor farmers in a village. So if, for instance, only 10 farmers can receive the “subsidy” in a village of 100 in that particular simulation year, a farmer will be deemed to have received if s/he is among 10 of the least resourced farmers (cash + food reserves) arranged linearly from the least resourced to the most resourced.

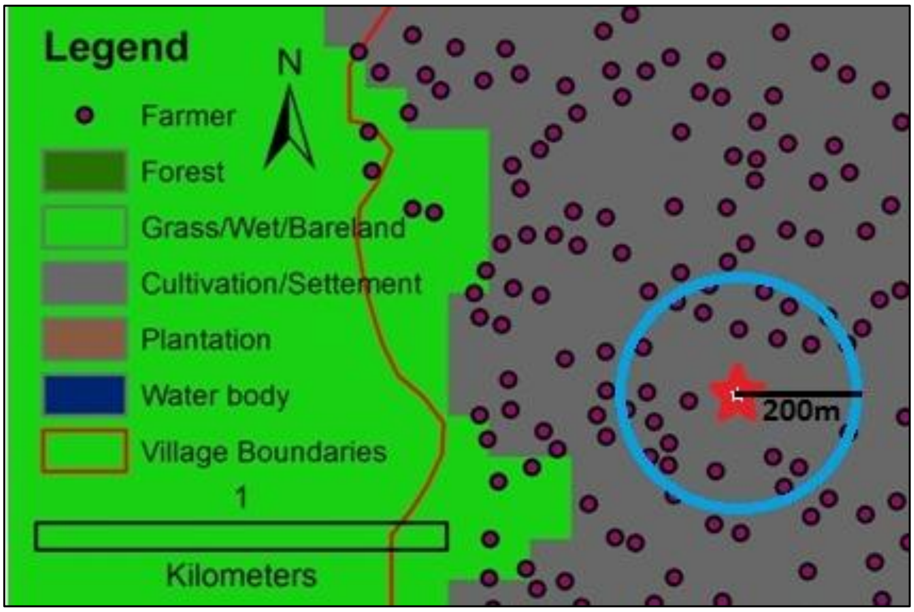

Figure 5-3: Simulating interaction between farm household (farmer) and extension worker (red star) agent

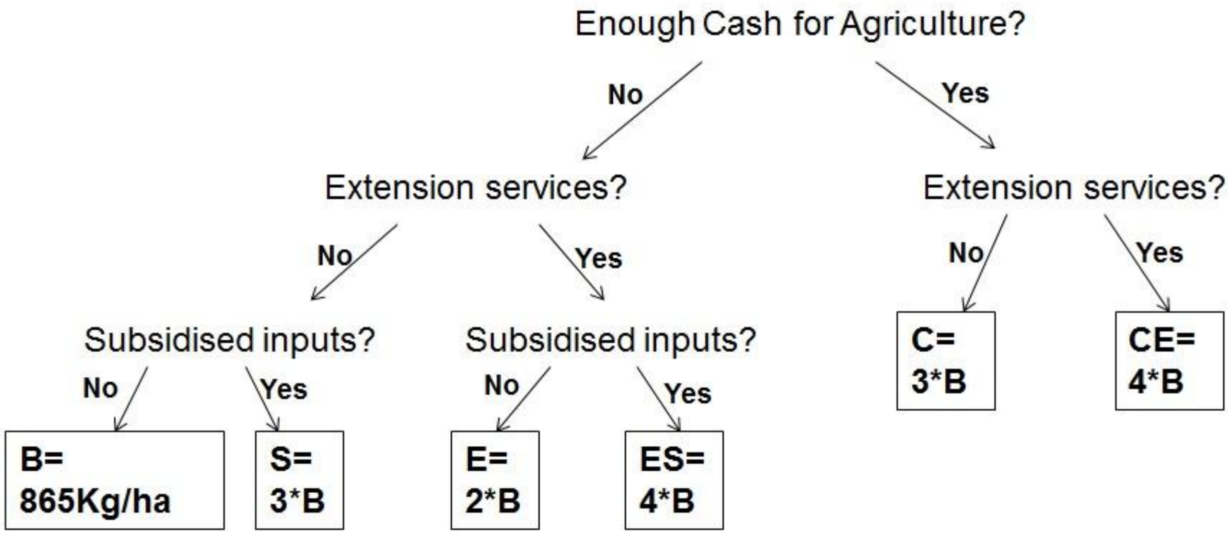

Figure 5-4: Farm household agent heuristic decision-making structure to "Grow crops" (maize/corn)

The household crop production estimates are then made as per the "leaves" of the heuristic decision tree shown in Figure 5-4. Each leaf correspond to varying levels of crop productivity depending on the availability of cash (to buy production materials), exposure to good farming methods (agricultural extension services), and access to subsidized production materials. The leaf **B** in Figure 5-4 represents the minimum basic production using local inputs (e.g. seeds kept from previous harvest), estimated at 865 kg/hectare for the year 2010 (Malasa D., personal communication, 14 April 2011). This corresponds to a household that does not have access to any of the resources. **ES** and **CE** represent four times the production capacity of **B** by employing new farming techniques with the added advantage of using at most a quarter of the required inputs (cash saving) and having its own fuel wood (World Agroforestry Centre 2008). **S** and **C** are equivalent to three times the basic production capacity while **E** is just double **B** (Malasa D., personal communication, 14 April 2011).

The biophysical factors determined where exactly the deforestation should take place. The household's decision to produce charcoal is partially dependent on food or cash deficiency (food produced against food required for the household) and partially random for the reason that not every household having a food or cash deficit engages in charcoal production. Literature for the study area has no specific statistics on the percentage of households who decide to engage in charcoal making when in food or cash deficit. However, an analysis of the field survey data revealed an approximately 40 % chance that every household in food or cash deficit will opt for charcoal making. Figure 5-5 is a flowchart highlighting the spatial logic of how the deforestation was simulated.

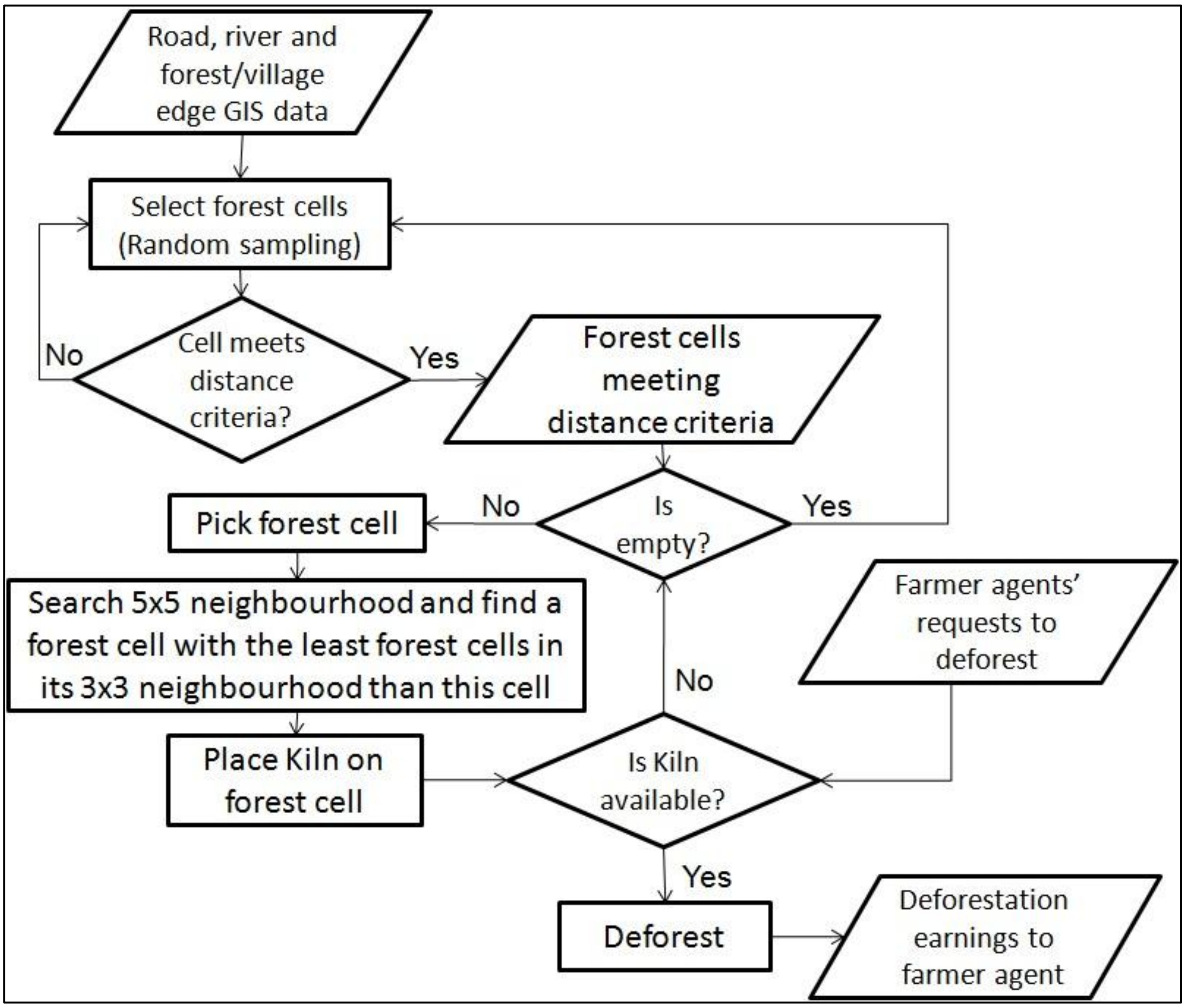

Figure 5-5: Logic of the kiln agent representation

The distance criterion in Figure 5-5 picks a forest cell that is closest to the three biophysical driving factors of deforestation. Figure 5-6 shows how the simulation enforced deforestation contiguity (i.e. minimize salt-and-pepper). The 5 × 5 neighbourhood of each forest cell picked by the distance criterion (represented by cell **a** in Figure 5-6) is searched to locate forest cells that have the least number of forest cells in their 3 × 3 neighbourhood than in the 3 × 3 neighbourhood of this particular forest cell **a**. In Figure 5-6, if forest cell **a** meets the distance criterion there exist forest cell **b** in its 5 × 5 neighbourhood. In this case, even though forest cell **b** may not meet the distance criterion like **a**, the simulation would opt to deforest forest cell **b**. Because **b** has more non-forest cells surrounding it than **a**, the simulation assumes **b** has higher probability to be deforested. The actual deforestation occurs if and only if a household agent exists that has signalled that it will deforest as a mechanism to cope with food deficiency.

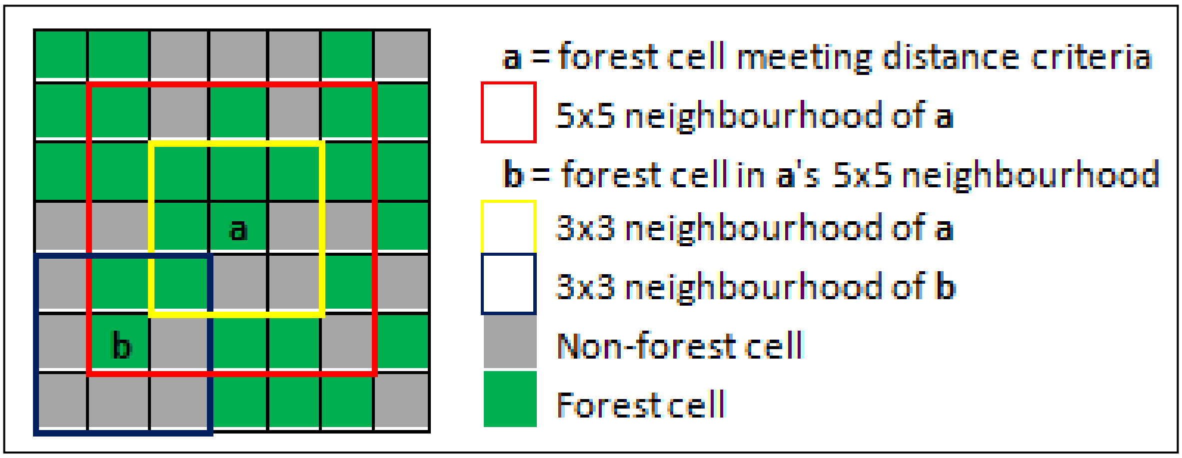

Figure 5-6: Enforcing forest loss contiguity

5.4 Simulation Results

The deforestation trends for Dzalanyama forest reserve were simulated over a 40 year period beginning in the year 1990. Two scenarios were considered in which smallholder households grow crops as their main economic activity and only engage in charcoal production as a coping mechanism against food/cash shortages. The two are the business as usual scenario (S_1) and the increased reward from charcoal production scenario (S_2). In S_1 the conditions are that i) the retail price of charcoal will be pegged at the prevailing estimated market value per bag (see Figure 3-5) of MWK2000 (~US$8); ii) the number of extension workers will be as it stands - one per section of the EPAs instead of the recommended two per section due to under-staffing (Malasa D., personal communication, 14 April 2011; see Table 3-1); and iii) there will be 31,200 recipients of subsidized production materials.

In S_2 the conditions are similar to S_1 except for the increased reward from charcoal production which was simulated as an assumed increase in the retail price of a standard bag of charcoal by 50 % (pegged at MWK3000 from MWK2000).

5.4.1 Validation

5.4.1.1 Farm household and kiln agents

Figure 5-7 shows the percentage of total households that are food deficient between the time steps 1 (1990) to 20 (2010). Between 1990 and 2003 it fluctuates between 70 and 80 % which are on the higher side compared to national food deficiency estimates that fluctuate between 40 and 65 % (Government of Malawi, 2005) for rural poor households. However, the 40 – 65 % deficit is comparing household food produced against area average production while in the simulation I compared the amount of food the household produced against what it requires for the time step. This suggests that the national food deficiency estimates are an underestimation. Upon the re-introduction of FISP in 2004 the simulated percentage of food deficient households dropped to around 50 % which is in tandem with the 40 - 60 % (Government of Malawi, 2005) for a similar period.

Figure 5-8 depicts the summed total of the number of times all the kiln agents relocated for each simulation time step up to time step 20 (2010). The frequency of the relocation is generally constant until 2004 when it drops slightly coinciding with the introduction of FISP that year. The cumulative relocation frequency trend depicts the accumulated kiln movements over the period. The cumulative relocation frequency value for the year 2000 (11,550) and 2010 (20,087) is almost the same as the number of hectares of observed forest loss for 2000 (13, 639ha) and 2010 (22, 031ha). This is because each kiln agent can occupy a single grid cell (100 $\times$100m = 1ha) and relocates when the grid it is occupying is depleted of its forest stock. This implies that each time a kiln agent relocates it will have deforested an extra hectare.

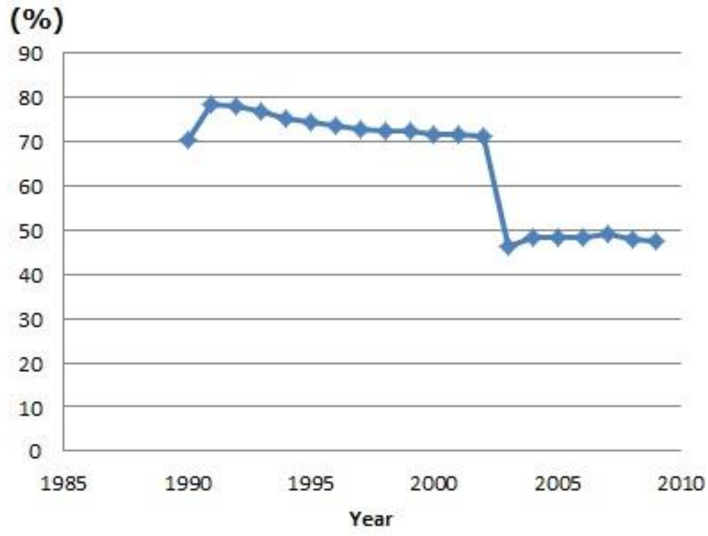

Figure 5-7: Percent of total number of food deficient households

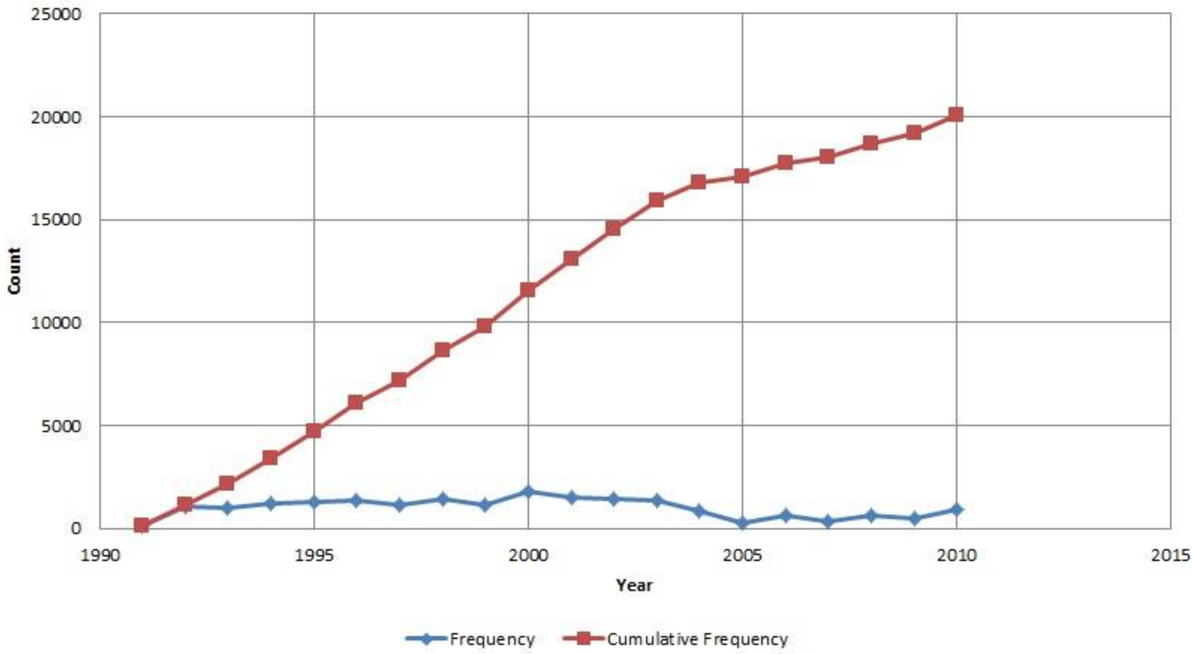

Figure 5-8: Frequency of movement of the kiln agent

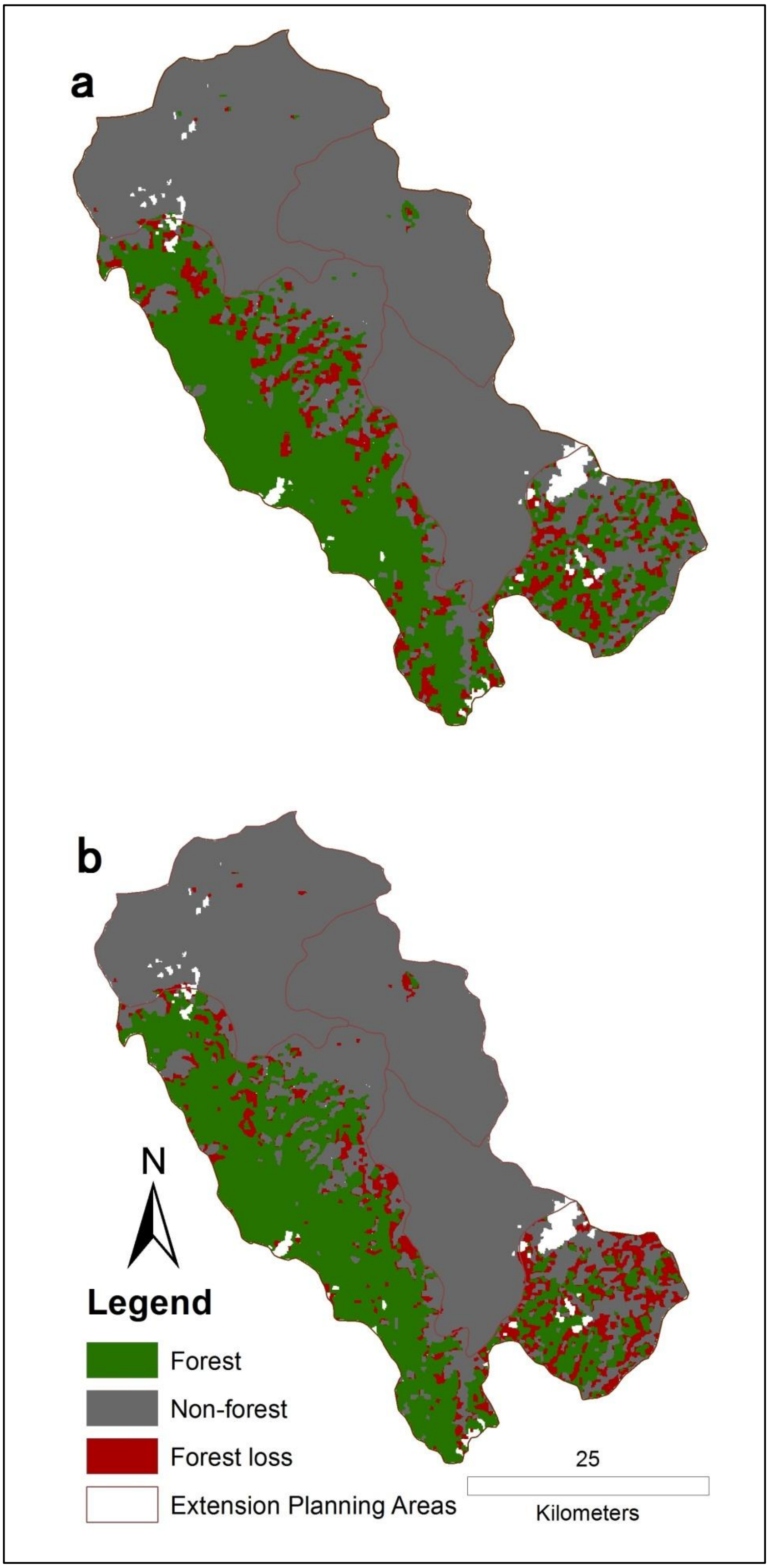

Figure 5-9: Forest loss 2000 as a) simulated with business as usual conditions; b) observed

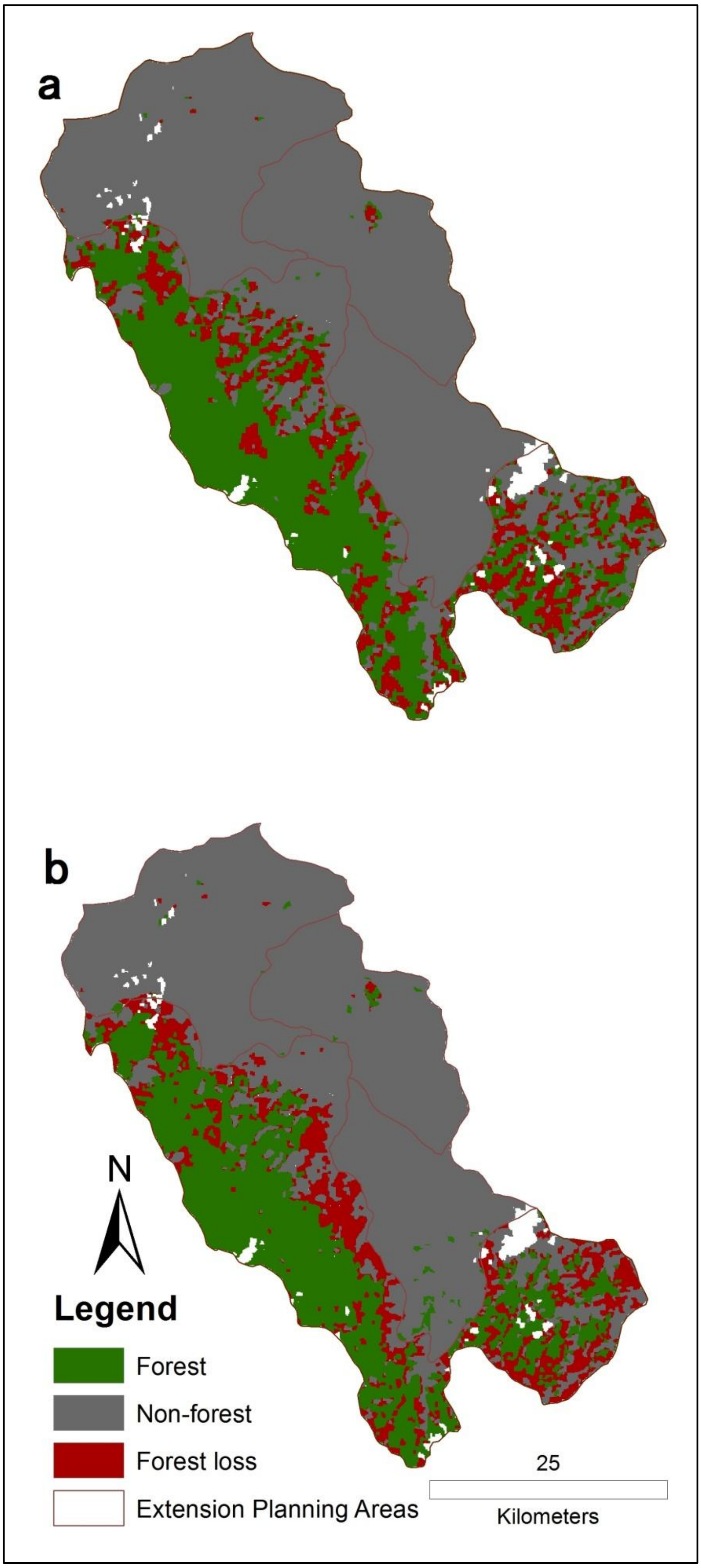

Figure 5-10: Forest loss 2010 as a) simulated with business as usual conditions; b) observed

5.4.1.2 Spatial accuracy

Figures 5-9 and 5-10 show the simulation results for the business as usual scenario for the years 2000 and 2010 compared with their respective observed land use maps. The number of hectares deforested is an emergent phenomenon from the interactions of the farm household agent and the kiln agent simulated as the relocation of the kiln agent. From 1990, 12,207 ha of forest were simulated as lost against 13,639 ha observed in 2000. This implies kiln agents relocated 12, 207 times from 1990 to 2000. The quantities accumulate to 19,459 ha simulated against 22,031 ha observed by the year 2010. Statistically, the simulation stands at a standard Kappa value of 0.731 and 0.629 when compared with the observed land cover map for 2000 and 2010 respectively.

Using Map Comparison Toolkit (Map Comparison Kit, 2012), the simulation does explain some land cover change (KSimulation = 0.192). The quantity accuracy, individual class (forest to non-forest) transitions similar for both the observed and simulated maps in 2010, stands at 82 % (KTransition = 0.815). While the number of times the kiln agent relocated determined the quantity accuracy, where it relocated to determined the spatial accuracy which stands at 24 %. That is out of all the forest to non-forest class transitions 24 % (KTranslocation = 0.235) were correctly allocated spatially (Hits in Figure 5-11). The simulation also compares very well with the biophysical driving factors as depicted in Figure 5-12. The spatial pattern is such that the farther you move away from the biophysical factors of river, road and the forest/settlement boundary the less the deforestation.

There are some very conspicuous "misplaced" errors (Figure 5-11, 2010), especially those occurring in the central area of the forest reserve. These could be attributed to forest edge/settlement distance factor, which used the 1990 classified image to define the forest/settlement boundary from the non-forest category (see Figure 5-1). The cells in the centre of the reserve may have been correctly classified as non-forest, however, they did not represent settlement areas. While most of the non-forest cells coincided with being settlements, especially those outside the designated forest reserve boundary (forest edge 1922, Figure 5-1), the derivation of the distance from forest/settlement boundary erroneously assumed these non-forest cells in the centre of the reserve to be settlements. As such when deriving the forest edge/settlement distance factor, the forest cells surrounding the non-forest cells erroneously assumed to be settlements were then considered to be close to non-existent settlements. In addition, because the river network is dense in the forest reserve, whenever these erroneous settlements coincided with roads the simulation picked them as potential areas of further deforestation.

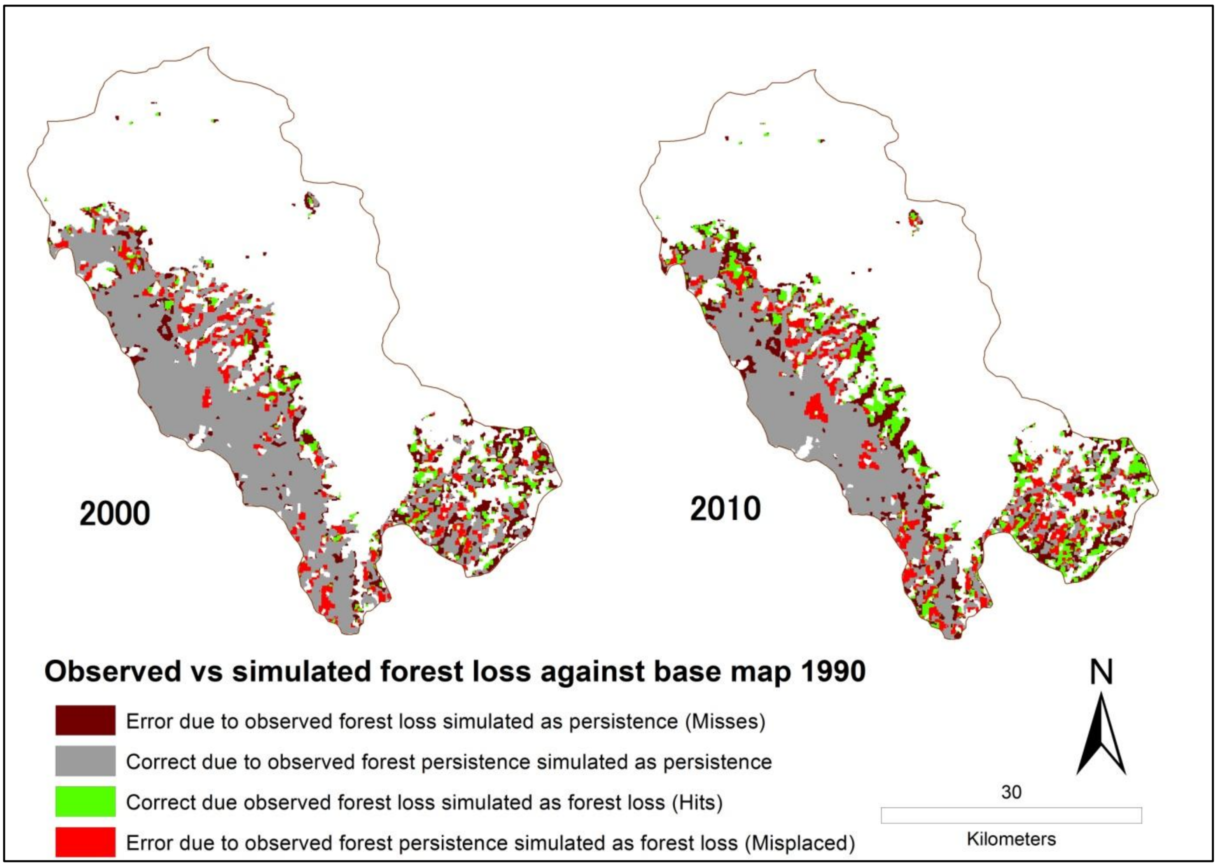

Figure 5-11: Simulated versus observed forest loss spatial distribution against base map 1990

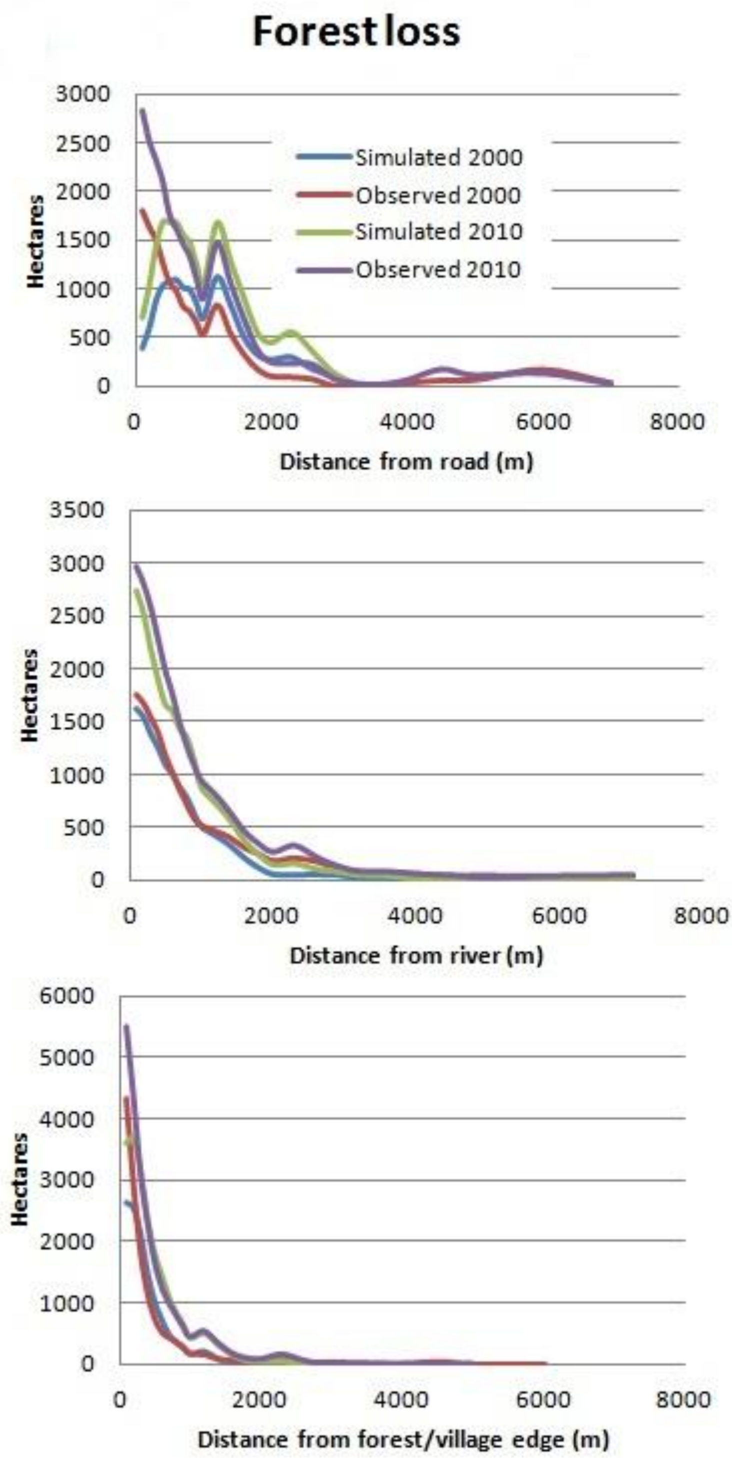

Figure 5-12: Simulated versus observed forest loss against spatial driving factors

5.4.2 Future estimates and scenarios

Based on the successful simulation for 2000 and 2010, I predicted future forest loss for 2020 and 2030 using S_1 and S_2 scenarios (Figures 5-13 and 5-14 respectively). The south-eastern part of the forest reserve will have lost almost all its forest cover by 2030 in both cases, with the deeper and further western side maintaining most of its forest cover. This spatial trend is understandable considering the influence of the driving factors as shown in Figure 5-12 for which the further the location is from each of the driving factors, the lesser the forest loss. The south eastern part has a dense network of both roads and rivers. The quantities involved are shown in Figure 5-15 alongside Markov chains predictions (from Figure 4-4). S_1 predicts forest loss of 23,100 ha by the year 2020, which accumulates to 26,721 ha in 2030. S_2 has reduced predicted forest loss of 21,676 ha in 2020 and 24,060 ha in 2030.

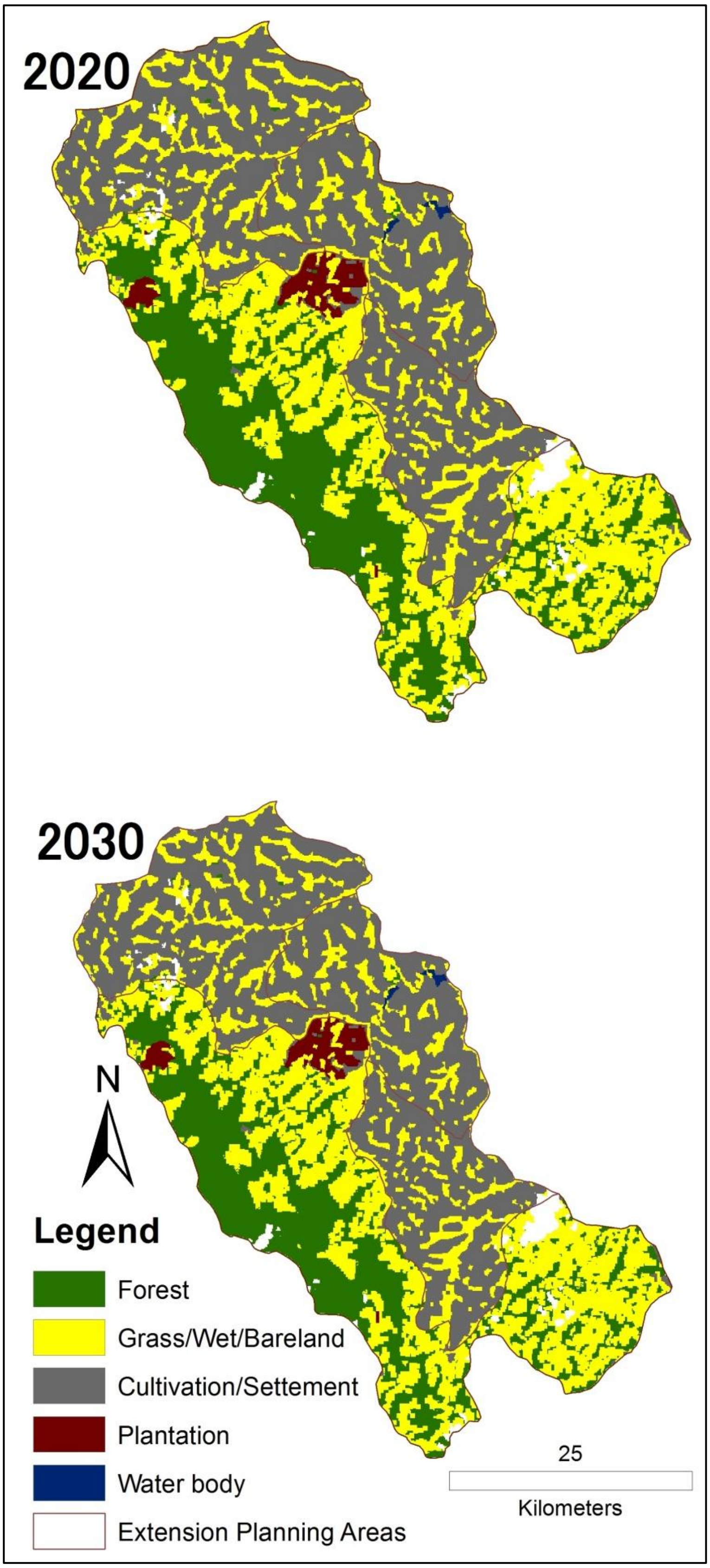

Figure 5-13: Predicted Land use/cover with business as usual conditions

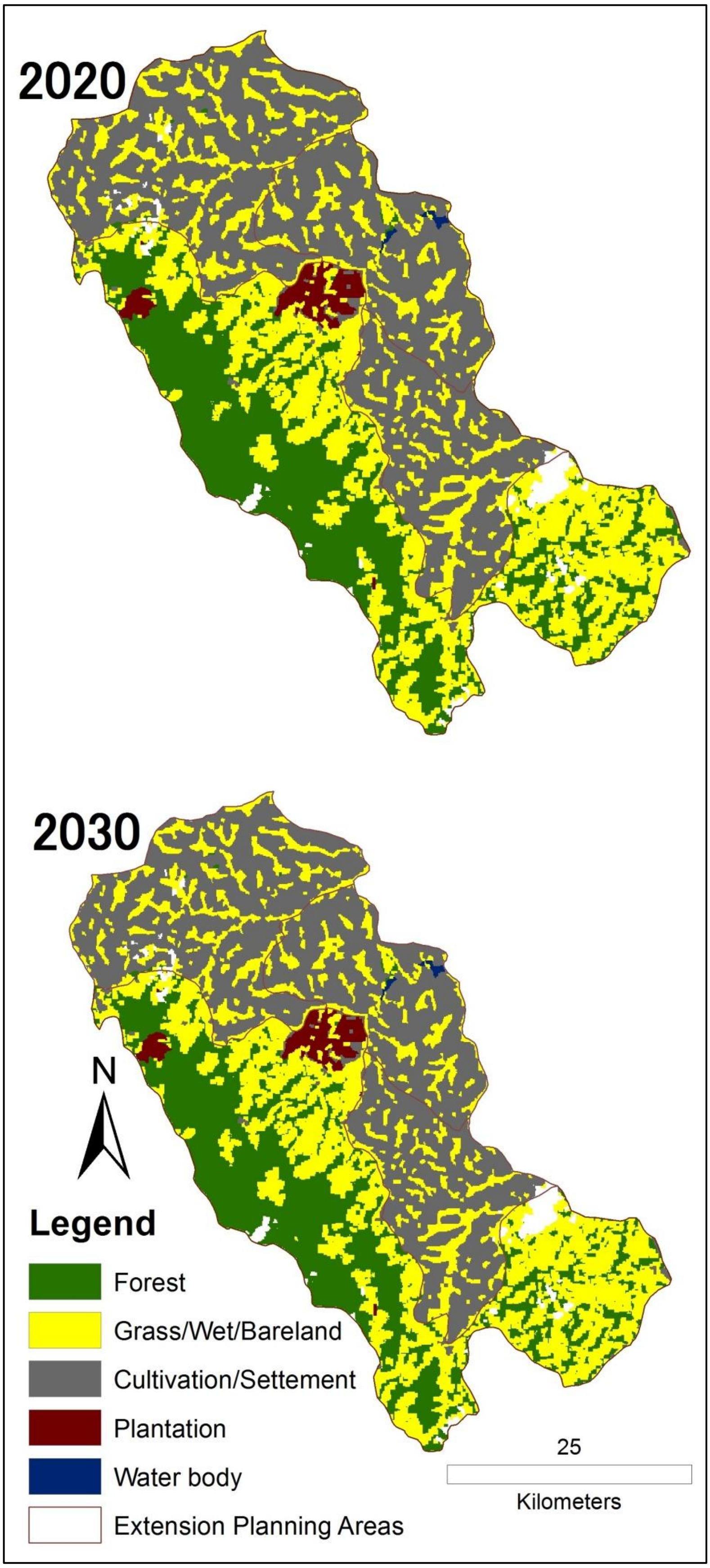

Figure 5-14: Predicted Land use/cover with a 50 % increase in income rewards from charcoal selling

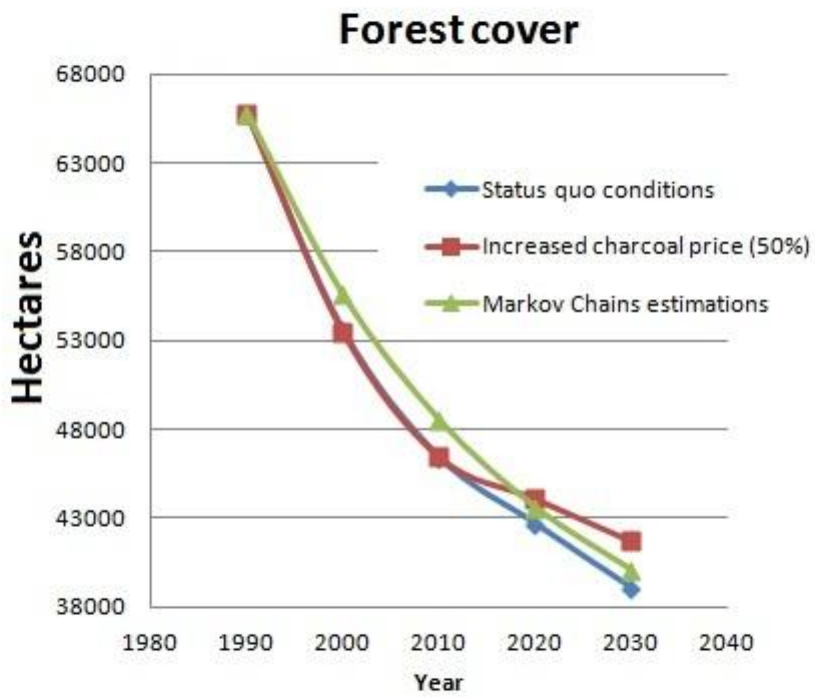

Figure 5-15: Quantities of forest loss predictions 2020 and 2030

5.5 Discussion

A MAS approach in which smallholder households in the study area make independent decisions to grow crops to sustain their households and how they cope with any shortfalls has demonstrated results comparable to observed deforestation trends and those reported in literature (Munthali and Murayama, 2011). Individual decision-making based on household composition, availability of production materials, access to subsidized production materials, and access to sustainable farming methods has shown great capabilities of MAS to encourage further exploration of this modelling approach in deforestation.

It should be mentioned that households' decision-making has no temporal memory of, for instance, past crop performances and as such the crops with which a household starts with in 1990 will be the ones it ends up growing in 2030. The heuristic decision-making is therefore based on the household’s available resources and the characteristics of its property at each particular point in time. The simulation implemented two off-farm income generating activities: 1) casual labour to represent all other forms of IGAs in which the households engage; and 2) charcoal production, the IGA that leads directly to deforestation of the forest reserve. Labour and land were assumed to be sufficient and soil conditions good as per survey observations. With these simplifications and assumptions the observed similarities between the temporal patterns of the simulated business as usual conditions and those observed through change detection using remote sensing techniques are therefore encouraging.

The solution to reduce the salt and pepper effect offsets the spatial accuracy of the simulation by at most some 280 m, as the scenario presented in Figure 5-6 represents the worst case possible given that the cell size was 100 × 100 m. This offset is very evident in the distance to road than river factor as shown in Figure 5-12. The forest loss shows an uncharacteristic positive correlation to increase in distance between 0 to 500 m of the road. This is understandable, though, given that the road network is less dense in the forest reserve than the river network.

The results in S_1 show close similarities with forest loss trends observed in Dzalanyama between 1990 and 2010 and provide a good basis to predict forest cover for 2020 and 2030. Food deficiency in the smallholder farming system is the major driving factor of quantities of deforestation in Dzalanyama. Despite FISP reducing the household food deficiency significantly (from around 70 to 50 %), its influence on the quantities of deforestation are less pronounced. With 50 % of the households still in food deficit it is therefore not surprising that this reduction does not affect the threshold number of households that resort to deforest which the field survey established to be between 30 and 40 %. This suggests that to have a significant influence on the quantities of forest being lost the focus should either be to ensure that the food deficiency levels drop below 30 % of all households or completely look elsewhere to contain the deforestation. The former is achievable through all the conventional and well talked about interventions that include moving to a universal as opposed to a targeted farm input subsidy program. Improving the smallholder agricultural practices to enhance the efficiency in the production has also been proposed through, for instance, increasing the infiltration of extension services (through increased numbers and better trained extension workers). However, despite being well proven and documented in reducing food deficiency and in this case even the deforestation, these interventions require substantial financial injections. These are financial resources governments in the developing world do not have or at least are never prioritised for the same. Malawi is no exception and as such though everyone knows what needs to be done nothing is being done due to lack of financial resources.

5.5.1 Containing deforestation in Dzalanyama

It would have been easy for this study to toe a similar line in proposing interventions as mentioned above to deal with the causes of the food deficiency that leads to the deforestation.

However, S_2 looks at the whole problem from a different perspective. If the biggest challenge to forestry management is finances, S_2 asks the questions: i) What would happen if the households/charcoal producers are allowed to be decently rewarded from their charcoal production efforts? and ii) What would happen to the overall deforestation if the charcoal production industry is allowed to generate finances for its own sustainable management? S_2 would somehow imply charcoal production becoming more economically attractive and therefore see more households venturing into it. However, the critical factor in the simulation is that the smallholder households are assumed (just as in S_1) to continue farming as their main traditional economic activity and not abandon the crop production and shift significantly towards charcoal production. This is achievable because, given that all production materials are available, farming is still regarded as a viable main activity for most of the rural households. Secondly, even if the households do shift, as Kambewa *et al.*, (2007) noted, the resultant unsustainable deforestation levels in most forest reserves in Malawi are not necessarily because the total charcoal supply is out of balance with the wood stocks. It is rather due to failure to provide incentives to manage wood production in a manner that allows regeneration in and around charcoal producing areas. S_2, therefore, simply presents a socio-scientific simple understanding of the positive influence that charcoal production that is generating formal revenue and handsomely rewarding for the charcoal producer would have on the overall system dynamics of managing deforestation of Dzalanyama Forest Reserve.

With the assumptions above, S_2 has shown a positive influence on the predicted amounts of future forest loss (2020 and 2030). The accumulated forest loss decreased by 1,424 ha (~6 %) in 2020 and 2,661 ha (~10 %) in 2030 when compared to the respective business as usual predictions. This reduction in forest loss represents an accumulated gain (or sustenance) of forest cover of 4 % in 2030. This accumulated gain can only increase by 2030 and the years beyond considering that the simulation did not include forest regeneration. S_2, as proposed in the simulation, suggests a possible way of mitigating the consequences (deforestation) of food deficiency induced charcoal production. While it was simulated as an assumed increase in the retail price of a standard bag of charcoal, S_2 does not propose a literal and solitary increase in the price of charcoal. It would not be easy to increase the price of charcoal literally given the economic dynamics of the study area. The socio-economic situation of the urban charcoal market is volatile and unpredictable. It is also a very politically sensitive issue for any sitting government to pursue as charcoal is used by the majority of the voters.

How then do we achieve the results of S_2 in reality without necessarily increasing the price of a standard bag of charcoal? The most important step is to regulate the charcoal industry (production, transportation and selling). With charcoal production still informal and illegal in Malawi, this step can only be achieved by formalizing and legalizing the production. The charcoal industry is big in Malawi despite being illegal. As charcoal is moved from point of production to markets, traders incur other costs that largely include private taxation by public officials (Kambewa *et al.,* 2007). These officials include people on duty on roadblocks and traffic police officers who often demand payments in cash or kind before they can allow the traders to pass with the charcoal. Formalisation of the charcoal industry will therefore, not necessarily introduce new and extra taxes but rather generally turn the private taxes into formal public taxes. This does not only guarantee that the taxation will not raise the charcoal prices (as the taxes already exist) but also a boost to central government revenue collection. Kambewa *et al.,* (2007) estimates that if charcoal were to be exported, its annual foreign exchange income to Malawi would fall somewhere between that of tea (Malawi's second largest export after tobacco) and sugar (third largest export).

Once regulated and substantial revenue collected, rules on efficient and effective charcoal production can be enforced allowing charcoal producers to make more charcoal from less wood stocks. More charcoal would mean the increased accruing income to the households as simulated in S_2 is achieved while less wood stocks would mean reduced wastage of fuel wood. The latter then will reproduce, in reality, the reduced future forest cover as simulated in S_2.

The result in S_2 provides backing for indeed pushing for formalization of the charcoal industry but from the standpoint of its influence on mitigating deforestation as established and not just for the purposes of boosting revenue collection as proposed by Kambewa *et al.*, (2007). This has the potential of making more financial resources available to both the charcoal producers and forestry authorities. In the long run, the forestry authorities would then have the much need financial resources that will enable them to enforce further and better sustainable forest management interventions and even introduce new ones like ecosystem service payment programs. Again with more disposable cash available, the charcoal producers/farmers can then begin to invest in better agricultural farming practices to increase crop production or better and efficient charcoal production techniques to reduce wastage of fuel wood. The former would significantly reduce household dependency on charcoal production while the latter would imply cutting fewer trees to sustain the households' needs. Either way the increased reward from charcoal production for the producer serves to reduce the deforestation in the long term. It should be mentioned, though, that a formalized and hence more rewarding charcoal production can in reality spur increased deforestation in the short term as the economic dynamism of the households would shift towards the more rewarding IGA. However, it would be expected to even out in the long term as attested by the results in this study.

Chapter 6

Concluding remarks

Explicit incorporation and articulation of linkages of smallholder production and consumption theories on the one hand with frontier tropical deforestation on the other has been the missing link in the present-day MAS approaches of LUCC and deforestation. Particularly in simulating agents of tropical deforestation acting from a distance. The work of Sulistyawati *et al.*, (2005) and the migration sub-model of Rajan and Shibasaki, (2000), however, significantly highlight the capabilities of future MAS to simulate household crop production-dependent off-farm activities, without necessarily relocating the agent. These off-farm activities more often than not include illegal forest felling which affects the overall trends in tropical deforestation. They can therefore, once successfully simulated, enhance our understanding of the tropical deforestation process in areas where there is no significant shifting cultivation or commercial logging.

Homogeneity of tropical smallholder farming activities is controversial and seems to be in direct conflict with the heterogeneous approach on which MASs are built. However, with explicit dynamism in simulating labour and land scarcity factors of the smallholder tropical regions, the small and slow individual homogenous practices at the household level can be incorporated and thresholds successfully attained. As such, with a slight shift in focus and expansion of scope to accommodate such homogenous environmental activities, MASs would best model the resultant trends in massive deforestation. Building on the sensitivity of MAS to small changes, D-MAS has demonstrated potential to magnify micro-scale decisions made at the individual farm level, exposing the trigger mechanisms of deforestation. By capturing farmers' interactions with the land-use system, D-MAS provides an important tool for insightful management of forest resources to avoid irreversible damages caused by deforestation.

The ecological landscape of Dzalanyama forest reserve is under massive degradation and the trends show no signs of abating if the situation is left unattended. Such rates defeat the whole essence of calling the study area a forest reserve. Much as population growth and poverty play important roles, the complex forces of changing economic opportunities have the most significant impacts on deforestation of the forest reserve. Massive forest loss is evident in the forest reserve area from the combined influence of: 1) the households' inability to meet their food and/or cash requirements from agriculture, their main activity; and 2) the households' engagement in charcoal production (deforestation) as a coping mechanism against the resulting food and/or cash deficiencies of (1) above.

Inefficiencies in the smallholder farming system are the major driving factor of deforestation in Dzalanyama and the future looks bleak in the business as usual scenario that is influenced further by proximity to road, river and forest/settlement edge. Substantial sustainable forest management efforts in the study area and in Malawi in general are hampered by limited resources. The study, therefore, proposes regulation of the charcoal production to increase both revenue collected by government and cash inflow accruing to the producers. The former would imply possibilities to invest in more sustainable policy interventions while the latter would significantly reduce household dependency on charcoal production (higher crop production) and cutting fewer trees (efficient charcoal production methods) to sustain the households needs. Either way, though the simulation puts the gains in forest cover at a mere 4 % in the medium term, the advantages of handsomely rewarding charcoal producers would go beyond this quantitative benefit in the long term.

D-MAS has built on the strength of MAS as a replicative tool to develop a deeper understanding of the situation of the deforestation trends of Dzalanyama Forest Reserve.

Although these results are encouraging in themselves, there is plenty of room for improvement. While the quantities involved may be satisfactory, the spatial dimension needs improvements. Inclusion of more biophysical factors, for instance elevation, would boost the determination of the optimal areas where the deforestation occurs. However, the issue of transition contiguity and translocation with which I grappled with during the development of D-MAS must also be taken into account. This introduced a trade-off between the need to enforce the golden rule in geography - closer entities are more similar than distant ones, in that the forest loss occurs in places close to areas that have already lost their forest - and the need to obey the dictates of the biophysical factors in determining where "best" the deforestation should occur. As such this translocational quagmire will still stand in the way in the future developments of D-MAS.

With the addition or extension of objects and/or agents, D-MAS is a potential modelling framework that could be utilized within other tropical forest areas, especially those in Southern Africa. Therefore, though developed primarily to derive understanding of the influence of individual farm-based crop production decision-making for Dzalanyama Forest Reserve area, D-MAS possesses the potential for application to other study areas in the sub-Saharan region and/or beyond.

Acknowledgements

I most sincerely thank Professor Yuji Murayama, my academic supervisor, for all the guidance, inspiration, motivation and support throughout my study. This dissertation tapped from his vast knowledge and experience through the many discussions, numerous comments and suggestions at the various stages of my research. His willingness to engage me in various activities provided me with much experience. His continuous dedication and commitment towards my research is immeasurable. Completion of this research is very much indebted to his patience, understanding and encouragement.

Special thanks should also go to Assistant Professor Takehiro Morimoto and Associate Professor Hiroyuki Kusaka for their valuable inputs to my research. Their lectures on GIS techniques were very helpful and so too were their comments and suggestions. I am equally grateful to the members of the dissertation examination committee (Professors Akira Tabayashi and Masaaki Kureha; Associate Professor Jun Tsutsumi; and Assistant Professor Takehiro Morimoto) for their constructive criticisms, comments and suggestions. Heartfelt appreciation should also go to the Government of Japan for granting me Monbukagakusho scholarship for the doctoral study period at the University of Tsukuba.

Furthermore, this study was made possible because of support from Lilongwe Agricultural Development Division, the Departments of Survey and Forestry for the aerial photographs and road data respectively, UNICEF-Malawi for the river data and USGS for the Landsat TM images for 1990, 2000 and 2010 of the study area. Special mention should go to Mr. Douglas Malasa, the Agriculture Extension Development Coordinator (AEDC) of Malingunde EPA. Without his support and commitment the field data collection exercise for the study would have been a nightmare.

Finally, I express my special gratitude to my parents and sisters for their prayers, encouragement and support. I would like to thank my numerous friends both in Japan and outside for their encouragement. I am particularly very much thankful and appreciative to my wife Delia for her enormous sacrifices, forbearance, encouragement and support throughout my study.

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Appendix

A-1 Field survey

A-1-1 One-to-one interview questionnaire

HOUSEHOLD CHARACTERISTICS (to farmers - household head) Form Number:____

1. What is your family size? ______________________________
    1.1. Who is the head of the household? ______________________________
    1.2. Age/sex of each family member (e.g. 24/M):______________________________
2. How many help in farming (age/sex e.g. 24/M)?______________________________
3. What is your level of education? mark the appropriate: [primary], [secondary] or [tertiary]
4. Overall, what is your income per year? (Consider income brackets)
5. How much food does your household require per year (unit!?)? ____________________
6. Do you have enough labour? [yes] or [no] (explain)
7. What is your primary occupation? (farming, teaching etc)________________________

FOOD PRODUCTION (to farmers & overall estimates of Extension planning area officers)

1. What is the size of you total plot (hectares)? ______________________________
2. What and how much do you produce from your plot? (e.g. maize/0.5ha, cassava/0.3ha)

____

____

3. Does this suffice for your household needs? [Yes] or[No]
4. If you answered NO in (3), why is that the case? (tick all appropriate answers)
    4.1. No access to hybrid inputs [ ]
    4.2. Lack of enough labour [ ]
    4.3. No access to government subsidised inputs [ ]
    4.4. Degraded soil condition [ ]
    4.5. Insufficient land [ ]
    4.6. Lack of knowledge of advanced agricultural methods [ ]
    4.7. Any other reason(s):
        4.7.1. ______________________________
        4.7.2. ______________________________
        4.7.3. ______________________________
5. If you answered yes in (3), why is that the case? (tick all appropriate answers)

5.1. I can afford hybrid inputs [ ]
5.2. Sufficient labour [ ]
5.3. Have access to government subsidised inputs [ ]
5.4. Sufficient land [ ]
5.5. Good soil condition [ ]
5.6. Have access to extension services (Name them) [ ] ____________________
5.7. I supplement with cash crops (Name them) [ ] ____________________
5.7.1. How and when do you decide to grow cash crops?
5.7.1.1. ____________________
5.7.1.2. ____________________
5.7.1.3. ____________________
5.8. Any other reason(s):
5.8.1. ____________________
5.8.2. ____________________

6. Do you produce yearly? [Yes] or [No]
7. If your answer to (6) above is no, why not?
   7.1. ____________________
   7.2. ____________________
   7.3. ____________________
8. Do you have any other sources of income/food apart from farming? [Yes] or [No]
9. If your answer is yes to (8) above what are they and when do you do these activities?
   9.1. ____________________
   9.2. ____________________
   9.3. ____________________
10. If your answer is no to both questions (3) and (8) how do you sustain your household?
    10.1. ____________________
    10.2. ____________________
    10.3. ____________________
    10.4. ____________________
    10.5. ____________________

A-1-2 Household composition data collection form

Lilongwe Agricultural Development Division, Malingunde EPA farming household characteristics survey January 2012.

Collector Name:____________________________ Date Collected:___________________

Name of farmer	Head of house	Total # of people (including parents)	# of Children		Total Farm size (acres)	Crop Distribution (acres)						
			<15yrs	>=15 yrs		maize	G/Nuts	tobacco	soybean	cassava	Sweet potato	other