Chapter 1
Land Change Modeling: Status and Challenges

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Abstract Over the past years, land change science has emerged as a fundamental component of global environmental change and sustainability research, and modeling of land change has been recognized as a premier research area in land change science. Various land change modeling approaches have been developed to explore the functioning of land changes at aggregated and individual levels, across various spatiotemporal scales, as well as in human, natural, or the coupled systems. This chapter will review a collection of land change modeling approaches including statistical regression models, artificial neural networks, Markov chain models, cellular automata, economic models, and agent-based models. For each approach, the theoretical and methodological basics and major characteristics will be examined. Moreover, several important issues challenging the successful implementation of land change modeling will be discussed, which include coupling human and environmental systems, scale dependency and multilevel interactions, and temporal dynamics and complexity. Finally, a review on the progress of integrating land change models with other environmental modeling techniques for global environmental change research will be provided.

Keywords Land change modeling • Land change science • Global change • Land use and land cover change • Coupled human-environmental systems

1.1 Introduction

The process of global change is altering the earth system and its capacity to sustain life (U.S. Global Change Research Program 2014). Rapid human population growth, along with their increasing demand for food, water, energy, and other

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benefits, has become the main drivers of global change, especially since the second half of twentieth century (Turner et al. 2007). Well-documented global changes include concentrations of carbon dioxide in the atmosphere; alterations in the biochemistry of the global nitrogen cycle; and on-going land use and land cover change (Vitousek 1994). Land use and land cover change is a pervasive factor of global importance not only because it represents a major component of global change but also it strongly interacts with other components of global environmental change. To date, as much as 50 % of the earth's ice-free land has been transformed or degraded (Haberl et al. 2007). Only between 2000 and 2010, approximately 13 million hectares of land area (about the area of Greece) were converted each year to other land cover types (FAO 2010). Moreover, land changes have far-reaching influences on the structure and function of the earth's ecosystems, with equally significant implications for the human society (Steffen et al. 2004). On the one hand, land changes affect the ecosystems in several ways, such as reducing native habitat and species, accelerating soil decomposition, disrupting freshwater resources and quality, as well as leading to additional greenhouse gas release (Turner et al. 1993; Camill 2010). For example, deforestation is thought to contribute to nearly 20 % of the global carbon dioxide release (1.5–2 billion tons of carbon) (Camill 2010). On the other hand, rapid urbanization and the concentration of human populations into large metropolises have altered the city's cultures, politics, and economics, which are just beginning to be fully recognized as a significant global problem.

Over the past years, land change science has emerged as a fundamental component of global environmental change and sustainability research (Turner et al. 2007). This interdisciplinary field seeks to understand land use and land cover dynamics through integrating the human, environmental, and geographical information-remote sensing sciences. Challenges lie in the complexity of land change processes, in which human and environmental systems interact over space and time to reshape the earth's surface. Research in land change science has been dedicated to enhance our understanding of land changes through: (i) monitoring land changes at different spatiotemporal scales, (ii) exploring the driving forces (both human and environmental) and feedbacks underlying land changes, (iii) spatially explicit modeling of land changes, and (iv) assessing system outcomes (Turner et al. 2007). Land change modeling is a promising research area which can support an integrated earth system science enterprise. Models allow us to link human behaviors with landscape patterns for simulating the processes of land changes in the past and present, for forecasting future landscape dynamics under different scenarios, and for informing decision-making towards sustainable land and resource management.

This chapter examines a collection of land change models (LCM) for global environmental change research. To a large degree, modeling is a way of thinking more than a technology. Over the past several decades, various modeling approaches have been developed, which provide insights into the functioning of land changes at aggregated and individual levels, across various spatiotemporal scales, as well as in human, natural, and the coupled systems. Meanwhile, there are numerous theoretical and technological challenges for the modeling of land changes given the complexity of the coupled human-environmental systems (Rindfuss et al. 2004). Advances in geospatial theories, technologies and data provide great opportunities for addressing various challenges and for developing the next generation of LCMs. In the following sections, we first discuss the theoretical foundations and major characteristics of various modeling approaches. We then identify some outstanding issues for the LCM communities. Finally, we describe several examples to illustrate how land change modeling can be coupled with other ecological modeling techniques for integrated global environmental change research.

1.2 Land Change Modeling Approaches

This section discusses several frequently used land change modeling approaches, including statistical regression models, artificial neural networks, Markov chain models, cellular automata, economic models, and agent-based models. The above modeling approaches were identified based on the authors' knowledge and a personal archive of relevant publications, and a search on Web of Science using the Keywords: (Topic = "land change" or "land use change" or "land cover change" or "land use and land cover change" or "urbanization" or "urban growth" or "urbanization" or "deforestation" or "farmland") AND (Topic = model or simulation). In the following subsections, we will briefly present the theoretical and methodological basics and the relative strengths and weaknesses of each modeling approach with selected examples.

1.2.1 Statistical Regression Models

The basic structure of statistical regression models is based upon empirical analyses that link between land use and land cover changes (i.e., dependent variable) and a set of environmental and socio-economic explanatory variables. The derived relationships are usually used to generate maps of land transitional probability to predict potential land changes in the future. Some frequently used statistical methods for land change modeling include logistic regression (Hu and Lo 2007), generalized linear models (Aspinall 2004), generalized additive models (Brown et al. 2002), and Bayesian statistics (Agarwal et al. 2005). A popular example is the CLUE-S (Conversion of Land Use and its Effects at Small regional extent) model developed by Verburg et al. (2002). The CLUE-S model consists of a non-spatial demand module and a spatially explicit allocation module. The non-spatial module estimates the aggregate demand of land changes, and the spatial module allocates the land demands at various locations on a raster space based on stepwise logistic regression. Logistic regression is a form of multivariate models when the dependent variable has a categorical output, e.g., change or no-change of land use. Logistic regression can be binomial or multinomial. It takes the logit transformation of the categorical dependent variable to ensure that the dependent variable of the regression is continuous.

Given the less demand of computational resources and easy operability, statistical regression models have become one of the most popular approaches for land change research communities. Statistical methods provide valuable information on key factors of land changes but are relatively deterministic compared to more advanced forms of model. It can also contribute to theory building and testing (Lesschen et al. 2005). However, it has very limited capability to represent the complex interactions and the temporal dynamics within the coupled human-environmental systems.

1.2.2 Artificial Neural Networks

Artificial neural networks (ANN) are developed based on machine learning algorithms (e.g., Li and Yeh 2002; Liu and Seto 2008). The functioning of ANN is relating to regression models in that they both seek to associate land change and its potential drivers. ANN is characterized by its 'learning' ability which can be used to detect non-linear relationships through the incorporation of a hidden layer. The algorithms of ANN calculate weights for input layers, hidden layers, and output layers by introducing the input in a feed-forward manner. For example, Liu and Seto (2008) presented an ART-MMAP neural network model for urban growth prediction from historical data. A set of proximity, neighborhood, and physical factors were included. This paper also applied a multi-resolution analysis to test the model's performance. In general, spatial aggregation results in higher accuracies. By comparing with a null model, two random models and a naive model, neural network outperforms other models at finer resolution.

The strength of neural networks lies in their flexibility and non-linearity (Lesschen et al. 2005) in predicting future changes. However, it provides little interpretability because the relationships between variables remain invisible, criticized as a "black box". ANN is commonly used for predicting future land cover/use changes based on the 'knowledge' learned from the patterns and behaviors observed from historical data. The assumption here is that past and present trend will continue into the future (i.e., stationarity), which tends to oversimplify the temporal complexity of land change processes.

1.2.3 Markov Chain Modeling

The Markov chain modeling approach employs a discrete stochastic process to determine the transition probability of land conversion. There is a set of discrete states in the modeling structure. In the context of land change modeling, each state usually represents different types of land cover/use. The model moves from one state (e.g., land cover/use type) to the other with some transition probability depending on the current state but not the previous ones (often called a process without memory). Transition probabilities are computed based on the observed land change data which represent the probability that the land cover/use type within a cell (i.e. spatial unit) will convert (or, move) to another land type within the same period of time in the future. For example, Muller and Middleton (1994) applied Markovian analysis to time series data to quantify land use changes over a human-dominated landscape. Markovian analysis can represent all the multi-directional land use changes between land use categories. Sequential time series data were used to simulate land use change over a longer time period.

Markov models usually do not account for specific drivers of land changes, which assume that collective forces functioning to produce the observed patterns in the past will continue to do so in the future. In other words, Markov models are used to project future land changes based on the assumption of stationarity. Markov model can be dynamic by changing the transition probabilities in some sort of regular patterns over time (Howard et al. 1995). Given the capability of automatically computing land transition probability with time series data, Markov chain models are often integrated with more complex forms of models such as cellular automata and agent-based model that will be discussed shortly.

1.2.4 Cellular Automata

A conventional modeling framework describes systems in equilibrium or as moving between equilibriums. However, the evolution of land changes usually does not reach a stable equilibrium but exhibits features of complexity (e.g., edge of chaos, emergence, and non-linearity). The concept of complexity emphasizes on the interdependence among constituent parts. Therefore, complex adaptive system (CAS) is a system composed of interconnected parts that as a whole exhibits one or more properties that are not obvious from the individual parts. Cellular automata (CA) models are built upon static cell-based environment where each cell has a state and can transfer to others based on the current state and the interactions with its neighborhoods using a set of transition rules (Batty and Xie 1994; Clarke et al. 1997; Miller and Page 2007). The four major components of CA therefore are state, landscape/space, neighborhoods and transition rules. For each of the four components, their structures vary from simple to more complex forms (e.g., Stevens and Dragicevic 2007). The transition rules are usually set to represent spatial and temporal constraints (Sante et al. 2010). One of the well tested CA models is the SLEUTH (Slope, Land use, Exclusion, Urban extent, Transportation, Hillshade) model developed by Clarke et al. (1997) for simulating urbanization. This model defines complex rules representing control parameters that allow the model to self-modify under the circumstances it generates. More applications of this model are found in Clarke and Gaydos (1998), Yang and Lo (2003), Jantz et al. (2004), Mahiny and Clarke (2012), and Akin et al. (2014).

As a dynamic modeling tool, CA model has gained great popularity among all modeling approaches. Although offering a framework for studying complex systems, CA modeling does not explicitly incorporate drivers of change except for the neighborhood interactions and transition rules. In addition, CA does not explicitly account for human decision makings in their modeling structures as the cells cannot move and their transition in states mainly represent the physical processes of land conversion.

1.2.5 Economic Models

Economic models generate land use patterns as aggregate outcomes from the underlying microeconomic behavior that determines demand and supply relationships. These models explicitly involve human choices and economic behaviors and thus address the human dimension of land changes, mainly focused on land uses. The basic idea of economic models of land changes is based on market equilibrium (e.g., market clear with zero excess demand and zero excess supply). Economic models can operate at aggregate scale (e.g., sector-based models) and disaggregate scale (e.g., spatially disaggregate models). Sector-based models represent the global economy and the interactions between different sectors (i.e., general equilibrium models) or only some specific sectors as a closed system (i.e., partial equilibrium models). Therefore, sector-based models describe the amount of land allocated to different uses by demand-supply structures (Sohngen et al. 1999). Spatially disaggregate models simulate the optimal land use decision based on profits or utility maximization or cost minimization (Bockstael 1996; Wu et al. 2004). These models explicitly represent individual decision-making at the micro level that will lead to land change outcomes at the aggregate level.

Economic models explicitly represent human land use decisions based on market and price mechanism compared with most statistical, machine learning and cellular models. The spatially disaggregate models are promising in accounting for the market feedbacks and dynamics within the land change systems. These models are often used in the agent-based framework to simulate the decision-making processes of human agents. Economic models are useful for non-marginal land change simulation and prediction. However, given the complexity of human choices and data scarcity, it is quite challenging for economic models to build the underlying assumptions.

1.2.6 Agent-Based Models

Agent-based models (ABM), or the multi-agent system models (MAS), are developed based upon the assumption that "agent" is the major driver of a system (e.g., Parker et al. 2003; Batty 2005; Torrens and Benenson 2005; Xie et al. 2007). ABMs are similar to CA models which are both spatial transition models built on a bottom-up perspective for the simulation of emergent properties of complex adaptive systems (Couclelis 2001). The three primary components of an ABM are the agents, landscape and their interactions. Within the modeling structure, the agents can interact with each other as well as the environment across multiple scales. Agents could employ high degree of rationality and information-processing ability in decision making which will influence the behavior of the systems (Miller and Page 2007). A number of ABMs apply the utility function to represent agents' decision-making on location choices (e.g., Brown and Robinson 2006; Xie et al. 2007; Ligmann-Zielinska 2009). Usually, an agent will select a location that can maximize the utility or profit. Although traditional ABM is built on the bottom-up perspective, researchers in geographic and ecological modeling have proposed that ABM should not be restricted to the bottom-up simulation (Xie et al. 2007). In the paper by Xie et al. (2007), the author considers both macro level and micro level spatiotemporal urban dynamics. The macro level model is based on a stepwise regression model to project the aggregated rate of change at township level. The micro level model is to allocate the changes at the cellular level. The interaction among the two levels is also modeled through incorporating township competition in the utility function.

The structure of ABM is promising for land change research in that it explicitly represents human-nature interactions and feedbacks which are essential components for simulating land changes as coupled human-environmental systems. However, given its complexity in model design and implementation, much effort needs to be done to examine its operability for simulating real world processes and to fully realize the potential of ABM. Moreover, the advancement of ABM is challenged by the lack of detailed data to represent and validate complex human decision-making processes and interactions among agents at the micro level.

1.3 Major Issues in Land Change Modeling

The usefulness and complexity of land change modeling lie in the necessity to treat land changes as coupled human-environmental systems with complex interactions and feedbacks at multiple spatiotemporal scales (Turner et al. 2007). This section discusses several important theoretical and methodological issues in land change modeling: (i) coupling of human decision-making and environmental conditions, (ii) scale dependency and multilevel interactions, and (iii) temporal dynamics and complexity. These proposed issues are important for developing a comprehensive understanding of land changes in an integrated framework for global environmental change.

1.3.1 Coupling Human and Environmental Systems

Land changes are both causes and consequences of earth system changes, including the biophysical and the socioeconomic processes. Models taking specific drivers into considerations have tried to include factors from both subsystems. One major challenge arises from the integration of data and processes representing biophysical conditions and human decision making. Difficulty lies in the different levels of aggregation and spatial unit of observation (Rindfuss et al. 2004). In social-demographic analysis, data are usually collected at some levels of aggregation, whereas direct measurements and remote sensing techniques have been more commonly used in extracting biophysical variables (Jensen 1983). As a result, research of the coupled human-environmental systems has to deal with the problem of (i) integrating different types of data (e.g., raster and vector), (ii) integrating spatial data at different scales, (iii) integrating spatial data from different dimensions (e.g., point, line, polygon), and (iv) integrating data acquired at different locations (Gotway and Young 2002). These four types of spatial data integration problems are often intertwined, which leads to even more challenges.

The issue of coupling human and environmental systems is also related to the scale issues in that statistical modeling and machine learning are designed at the scale of the coupled system as a whole while cell-based models can represent multilevel dynamics in both dimensions. Moreover, it is quite challenging to fully represent the processes in the human subsystems due to the lack of specific data on human decision-making and a high level of uncertainty. Towards a comprehensive understanding of the coupled system, the potential interactions and feedbacks within the land change system need to be incorporated in the models. In this sense, the structures of agent-based models and integrated models seem promising for integrating human behaviors and biophysical feedbacks. Its capability in representing temporal dynamics further facilitates the realization of simulating system feedbacks in land change processes.

1.3.2 Scale Dependency and Multilevel Interactions

Research on the coupled human-environmental systems is further complicated by the issue of scale dependency and the multilevel interactions within the system. One of the early steps in spatially explicit modeling is to identify an appropriate scale (e.g., extent and resolution) for analyzing the spatial phenomena, such as land changes. This is known as the Modifiable Areal Unit Problem (MAUP) in geospatial science, that is, the correlation between variables may change with scales

(Openshaw and Taylor 1979). The common approach to deal with the MAUP issue is to apply a multi-scale analysis to examine how the relationships among variables change with varying levels of aggregation and different ways of zoning (e.g., Veldkamp and Fresco 1997; Walsh et al. 2001; Evans and Kelley 2004; Hu and Lo 2007). Multilevel statistical modeling has also been used for analyzing land change driving factors at nested hierarchical levels (Hoshino 2001).

Land change modeling is further complicated by the potential interactions and feedbacks among different levels of processes (Verburg 2006). In simulating the multilevel interactions, the modeling frameworks of cellular automata and agent-based model allow for the representation and incorporation of processes at multiple levels. The current land use models focus on two types of cross-scale dynamics: top-down and bottom-up simulation. The top-down control is represented by the government policies and global interactions affecting land demand and growth suitability. From the bottom-up perspective, human makes decisions on land allocation which produces the aggregate land use patterns. Further exploration on their capabilities is needed given the challenges in theoretical development and data availability, as well as the high computing demand of agent-based modeling.

1.3.3 Temporal Dynamics and Complexity

Simulating temporal dynamics is another critical issue for land change modeling, which brings about the need to handle time lags and feedback responses in the temporal dimension of land change processes (Agarwal et al. 2002). Under the assumption of stationarity, statistical modeling and machine learning have very limited capability to represent temporal dynamics and complexity of the land change processes. They often assume the factors leading to the observed patterns and processes in the past will continue to do so in the future. This assumption is problematic as it is very likely the factors will alter their future behaviors given changes in the landscape or some exogenous conditions. To the contrary, the framework of cellular automata and agent-based models allows for the temporal dynamics to be considered as the behaviors at individual level may alter in response to landscape changes or incorporated external variables at each simulation time step.

The ecological and socioeconomic responses within the coupled human-environmental systems may not be immediately observable or predictable because the existence of time lags between the human-nature interactions and the appearance of ecological and socioeconomic consequences. To address this issue, a temporally lagged variable can usually be included in some models such as the statistical regression models. More complex models have the flexibility to represent time lags in land use decisions. For example, Irwin and Bockstael (2002) treat the interactions among neighboring agents making a residential conversion decisions as a temporally lagged process to better represent the real world decision-making processes.

1.4 Land Change Modeling for Global Environmental Changes

The use and integration of models will lead to a comprehensive understanding of the complexity of the coupled human-environmental systems (i.e., synthesis and assessment issues). In the context of global environmental change and sustainability science, increasing concerns are given to research on sustainability that can inform practice and decision making in planning and management domains. The development of the next generation of LCMs needs to take these concerns into consideration towards an integrated research framework for land change and earth system studies. In this section, we review four research articles that illustrate the progress of coupling land change modeling with other environmental analysis and modeling techniques for studying the interactions between land change and other components of global environmental changes, such as climate change, hydrological processes, soil degradation, and biodiversity loss.

Kerr et al. (2003) described an integrated process-based modeling approach that couples ecological modeling of Carbon dynamics with economic modeling of land use for the prediction of land use and Carbon storage. This integrated model contains three components to simulate the interactions and feedbacks between ecosystems and human land-use activities. The ecological model and economic model were coupled through the land manager's choice of land use at each time step. The complex interactions were then realized through the exchange of individual model outputs as endogenous variables that will affect the next step of simulation. For example, the ecological model provides inputs to the land use choice model through estimates of biomass productivity. The key outputs from the integrated model include both land use and Carbon stocks.

Lin et al. (2007) developed an approach for modeling the impacts of future land use and climate changes on hydrological process through integrating the CLUE-S model (Verburg et al. 2002) and the generalized watershed loading functions model (Haith and Shoemaker 1987). The structure of the CLUE-S model was described earlier in Sect. 1.2.1. The hydrological model is a combined distributed/lumped parameter watershed model that simulates runoff, sediment, and nutrient loadings in a watershed using variable sized source areas of different land use/cover types. The simulated land use/cover types have different coefficient values that are used to determine the evapotranspiration in the hydrological model. Moreover, climate change scenarios generated from general circulation models (GCM) simulations have also been included to examine the impacts of climate change on the hydrological cycle.

Van Rompaey et al. (2002) loosely coupled land use change model with soil erosion model to predict future soil degradation and its on-site and off-site consequences. They firstly applied stochastic simulations to simulate future land changes based on the calculated afforestation and deforestation probabilities from historical land use maps. Then a spatially distributed soil erosion/sediment delivery model, SEDEM, was used to quantify the effects of afforestation or deforestation on soil erosion and sediment delivery. Land use classes are not directly involved in calculating the soil erosion component of SEDEM. But the probability of land conversion and soil erosion rate are both affected by the same factor of slope gradient. The simulated future land use patterns were used as input for the sediment transport component in SEDEM, with a transporting capacity coefficient estimated for each land use class.

Reidsma et al. (2006) assessed the relationship between land use intensity and related biodiversity in agricultural landscapes. For land use simulation, an integrated model was applied to quantify the area changes in agricultural land use and the CLUE model was used for land use allocation. Biodiversity in this study was measured using the ecosystem quality, which is expressed as the mean abundance of species originally present in the natural ecosystems relative to their abundance in undisturbed situations. Following the land use scenarios, the ecosystem quality of agricultural landscapes can be calculated as conditioned by land use. Then the impact of agricultural land use changes on overall biodiversity was assessed by comparing the relative size of nature area and the average ecosystem quality of natural ecosystems.

1.5 Conclusions

Land changes are processes in which human and natural systems interact over space and time to reshape the earth's surface. They are both causes and consequences of global change that interacts with other components of the earth system. Land change science has recently emerged as a fundamental component of global environmental change and sustainability science. However, the complexity of land systems leads to many challenges for the research communities. Among the research components in land change science, land change modeling appears to be promising in improving our understanding of land use and land cover change as a coupled human-environmental system.

A wide variety of modeling approaches has been developed to simulate the processes of land changes. This chapter has reviewed some commonly used approaches, including statistical regression models, artificial neural networks (ANN), Markov chain modeling, cellular automata, economic models, and agent-based models (ABM). These different approaches are built upon various theoretical and methodological foundations. The order of these approaches generally represents the theoretical transition of land change modeling from aggregate to individual modeling frameworks. The best model to use depends on specific applications given their unique strengths and weaknesses.

The complexity for land change modeling is owing to their need to represent the spatiotemporal dynamics of the coupled human-environment systems. For coupling the factors from human and environmental systems, development of data integration techniques can help address the differences in spatial data. However, more comprehensive understanding and representation of the integrated processes within the coupled system is one of the major challenges for land change modeling. To deal with the influences of spatial dependency, multi-scale analysis is necessary to address the Modifiable Areal Unit Problem (MAUP). Another important issue is to model the interactions and feedbacks among multiple scales in the land change processes. New models need to take into consideration of the multilevel processes and to integrate alternative perspectives into the existing modeling framework. In modeling land change processes, a temporally dynamic modeling framework is critical to capture the necessary behavior changes during the modeling time periods. Moreover, the factor of time lags needs to be considered to avoid biased simulation.

The advances in land change modeling offer great opportunities to study global environmental change in an integrated framework. The examples reviewed in this chapter should shed light on the progress of coupling land change modeling with other ecological modeling and analysis techniques for analyzing the interactions between land changes and other components of global environmental change. Many of the integrated frameworks are based on the use of simulated land use patterns or other land use/cover derived variables as input to the ecological models. More complex examples make use of the process-based models that integrate land change models and ecological models through individual decision-making using outputs from each model.

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