

A Review of Methodological Integration in Land-Use Change Models

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ABSTRACT

Global change research communities are paying increasing attention to answering critical questions related to land-use change, questions which are at the root of many pressing socio-economic and environmental issues. In this regard, a huge number of models have been developed to support future land-use planning and environmental impact assessments of land-use change activities. Within land-use change models, methodological integration is recognized as an essential feature for a complete model, which can help to combine the strength of single modelling methods/techniques without inherent weaknesses. Despite the potential and remarkable growth of methodological integration in land-use change models, limited attention has been paid to this aspect of integration. In response to this, the authors' paper summarizes the current major land-use modelling methods/techniques, and explains the co-integration of these methods/techniques. In addition, they summarize the achievements, limitations and future trends in the use of the methodological integration approach in land-use change models.

KEYWORDS

Integrated Approach, Land-Use, Land-Use Change Model, Land-Use Management, Land-Use Modelling, Methodological Integration, Review

1. INTRODUCTION

The Millennium Ecosystem Assessment (MEA) (2005) revealed that the modification and conversion of land by humans is among the most important and major global changes of the last three centuries. During this time, half of the Earth's ice-free land surface has been transformed by man. Most of the remainder is managed for human purposes unpredictably in terms of pace, magnitude and spatial scale (Global Land Project, 2005a). The MEA found hardly any uses of land that did not have negative effects on ecosystem patterns and processes across the terrestrial biosphere, including on the water cycle (Sterling et al., 2012; Swartz et al., 2003), soil environment (da C Jesus et al., 2009) and biodiversity (Hof et al., 2011; Seto et al., 2012; Zorrilla-Miras et al., 2014). Changes of the land surface have also disturbed the balance of greenhouse gases and resulted in the Aledo effect, which ultimately has contributed to regional and global climate change (Cai et al., 2004; Chhabra et al., 2006; Pielke, 2005; Rindfuss et al., 2004; Steffen et al., 2005; Wu et al., 2014).

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Given continuous population growth, sustainable land-use management has become ever more essential to human life (Global Land Project, 2005b). The need for sustainable land-use management has resulted in the development of models that describe and explain the process of land-use change, predict future scenarios, and measure the impact of land-use activities (Turner et al., 1999; Veldkamp et al., 2001; Verburg et al., 2004). Currently, the principal aim of land-use science is to project changes to land-use, an aim which helps natural resource managers and decision-makers make long-term, comprehensive and sustainable plans (Ghaffarzadegan et al., 2011; Helming et al., 2011; Müller, 2003; Parker et al., 2003; Pontius Jr et al., 2001; Reidsma et al., 2011).

With the progress in computing power, the integrated approach has emerged as an important means by which to improve comprehensive understanding of land-use dynamics (Rotmans et al., 2001; Verburg et al., 2006). The integrated approach varies with the model purpose, for example spatial integration; sectoral integration; land use type integration; economy-society-environment integration and methodological integration etc (Briassoulis, 2000). In this review, we concentrate on methodological integration, which is one of six essential features for a complete land-use change model as stated by Verburg et al (2004). Despite of its importance, there is very limited attention has been given to methodological integration within land-use change models. Methodological integration in land-use change models can be defined as the combination of more than one technique/method to better develop simulation algorithms in land-use change models. This approach gives detailed coverage of several essential aspects of the land-use change process, something that single methods fail to do. Methodological integration was analysed in the reviews of Briassoulis (2000); Heistermann et al. (2006), Koomen et al. (2011), and Michetti (2012). Nevertheless, these reviews focused only on the integration within operational models, which was established as a model package. Indeed, a large number of researchers have developed their own models rather than use operational models, given restricted scope and scale in the application of operational models (data and knowledge requirements, for instance). Reviews that focus only on the operational model do not cover the diversity of the methodological integration in land-use change models.

To fill this gap in knowledge, we reviewed methodological integration in both operational non-operational land-use change models. We summarized and synthesized knowledge and information from previous studies in the field to explore four key areas: (1) major modelling methods/techniques and their strength and weakness; (2) methodological integration in land-use models; and (3) the achievements and limitations of the methodological integration and future trends in this regard. A search of Scopus and Web of Science revealed that research in the field of land-use change began in the 1960s, and has continued since then. We consulted 30 of the most-cited articles and books written in the research field during this period. The references in these sources suggested further sources to examine. Our review paper is aimed at researchers or modellers who intend to improve their models or are looking for new research approaches but do not have much time to review a wide range of land-use change model research. Just by referring to our paper, readers will have a general picture and can find the appropriate methodological integration for their current and future works.

2. CURRENT LAND-USE MODELLING METHODS/ TECHNIQUES: STRENGTH AND WEAKNESS

An important consideration in model building is the selection of appropriate methods and techniques. The methods and techniques needed depend entirely on the purpose of the model or the research questions under investigation. In this section, we analyse the strength and weakness of major modelling methods/techniques currently employed in land-use change models. In addition, origin and general characteristics of methods/techniques are also introduced. In Figure 1, the development of methodological integration in land-use change models was summarized with a relative timing.

2.1. Cellular Automata Model

Cellular Automata (CA) was introduced by Ulam and Von Neumann in the 1940s to investigate the behaviour of complex self-reproducible systems. Then Tobler (1979) was the first person to apply CA in the field of geography. The strength of CA is that it is one of the simplest among methods suitable for modelling land-use change in a spatial and detailed fashion (Lagarias, 2012; Lambin et al., 2006; Yu et al., 2010). It has been used in many land-use change models (Jantz et al., 2005; Pinto et al., 2007; Stevens et al., 2007; Subedi et al., 2013). CA is based on mathematical theories of self-reproduction in automata and stochasticity within the two dimensional cellular-grid environment (Hewitt et al., 2014). The five elements of CA are cell space, cell states, time steps, transition rules, and neighbourhood, which influences the central cell (Moreno et al., 2009). After determining the number of cells that change in each step of the simulation, transitional rules are used to explain land-use changes based on the state of cells in the vicinity (Maria de Almeida et al., 2003). The transitional rules can be expert-based or derived from statistical analysis (White et al., 2000).

The popularity of CA rose with developments in remote sensing and GIS. Along with the benefits of interactive visualization and quantified outcomes, CA integrates easily with the GIS environment and remote sensing data (Han et al., 2009; Li et al., 2000; Sui et al., 2001). A widely used CA operational model is SLEUTH (Slope, Land use, Excluded land, Urban extent, Transportation and Hillshade), which has been successfully applied worldwide for over 15 years (Chaudhuri et al., 2012; Clarke, 2008). In SLEUTH, the land behaves like a living organism and is trained by growth transition rules (Herold et al., 2003). The multiple simulations of growth within SLEUTH are generated by the Monte Carlo theory (Jantz et al., 2005). The Countervailing Cellular Automata (CVCA) model also follows CA concepts. CVCA is defined by grid space, neighbourhood effect, a set of transition rules, and a time step iteration. In CVCA applications for land-use research, basic cells usually correspond to land-use types and transition rules to the processes associated with land-use change. The CVCA code is closely linked to SLEUTH and can work in conjunction with it (Silva et al., 2008).

CA models, however, focus more on the simulation of spatial patterns rather than interpreting the temporal process of socioeconomic variables (Hu et al., 2007). This bottom up approach might not be suitable for land-use systems where the area of land-use change is at least partly determined by demand for the activity carried out in the cells. The simplicity of CA allows it to integrate with other methods/techniques to produce a comprehensive model that encompasses the multiple effects of socioeconomic driving forces (Clarke et al., 1998; Herold et al., 2003; Li et al., 2000). These forces are discussed in the following sections.

2.2. Markov Chains Model

The application of Markov Chains to predict land-use change was proposed as early as 1965 (Briassoulis, 2000; Houet et al., 2006; Irwin et al., 2001). Using a 'stationary' assumption, whereby the temporal rate of change and actual change stay the same, Markov Chains employ matrices to present multi-directional land-use change in all mutually exclusive land-use categories (Lantman et al., 2011). For example, three land-use categories make for nine possible changes in land-use. The transition matrix can be created using expert knowledge or by drawing on history and maps and comparing land-use change over time (Muller et al., 1994). The transition matrix generates the transition probability, which is the probability of land shifting from one land-use type to another. In the earlier stages of land-change analysis, Markov Chains were used to estimate the total area of change with regard to particular forms of land-use, for example, urbanization in agricultural areas (Muller et al., 1994). More recently, analysis that uses Markov Chains has been combined with GIS to create a tool for visualizing and projecting the probabilities of land-use change (Ma et al., 2012; Munthali et al., 2011), assessing the relation of land-use change and climate change (Freier et al., 2011), and calculating the ecosystem service value of land-use (Luo et al., 2014).

The applicability of Markov Chains in land-use change modelling is promising because of its ability to quantify not only the states of conversion between land-use types but also the rate of

conversion among the land-use types (Subedi et al., 2013). In addition, Markov Chains can help to cover a larger spatial scale (Weng, 2002). However, Markov Chains modelling method is purely non-spatial; only cell states are considered and no attention is paid to the influence of neighbour cells.

2.3. Economic based Model

Economic based models of land-use change originated in the land rent theories of Von Thünen, proposed in 1826 (Helming et al., 2011). These theories referred to distance and transportation costs to explain land-use patterns and land prices. In general, economic science posits that resources will be allocated so as to maximize profit. The same notion can be applied to land-use. Economic based land-use change models incorporate the assumption that landowners will use the land in such a way as to maximize its utility and their expected returns. Land is allocated according to economic variables such as food consumption and prices, travel times and access to markets. Most economic based models of land-use change are equilibrium models, meaning that they seek to explain land allocation through reference to demand–supply structures (Michetti, 2012). GTAP, AgLU, and FASOM are widely used economic based models that employ the equilibrium theory to estimate land demand (Hertel, 1997; Michetti, 2012).

The strength of these economic models, which incorporate assumptions about future economic activity, is their description and quantification of drivers that affect demand. These models provide a structure by which to represent the competition between different sectors, changes in management and technology, and the shifts in demand that result from trade and policy interventions (Heistermann et al., 2006).

There are drawbacks to economic based models. They do not take into full account the geographic location of land (Verburg et al., 2003). Furthermore, results produced by economic based models rest on the assumption that economics is the main driver of land-use change: such models have tended not to account for climate and biophysical factors. Land-use change is a multidisciplinary issue, not attributable to economic variables alone. In addition, economic models assume homogeneity of all conditions within the study area and cannot account for impacts of land use change on land productivity as result of expansion on or abandonment of marginal lands.

2.4. Statistical based Model

Statistical based methods are used to derive the mathematical relationship that links the probability of land-use change with a wide range of variables such as population growth, topography and transportation corridors. These relationships are normally obtained through linear regression, binomial logit and multinomial logit models, and the logistic regression model (Takamatsu et al., 2014). The CLUE model, for instance, uses multiple regression to simulate recent and future changes in land-use patterns. The CLUE framework has been adjusted and applied to different study areas, using various versions of the model: CR (Veldkamp et al., 1996), CLUE-S (Verburg et al., 2007; Wassenaar et al., 2007) and Dyna-CLUE (Lourdes et al., 2011). Other statistical based models are Land-scanner (Hilferink et al., 1999), and FORE-SCE, which uses logistic regression to develop probability-of-occurrence surfaces for land-cover types (Sohl et al., 2008).

Statistical approaches have strength in modelling individual behaviours. These approaches can readily identify the influence of independent variables and also provide a degree of confidence regarding their contribution. In many cases, these models fit spatial processes and land use change outcomes reasonably well (Hu et al., 2007)

Many integrated land-use models are based on an extrapolation of trends in land-use change, determined through the use of a regression. Therefore, these models are not necessarily suited to longer-term scenario analysis as they are based on a limited period, usually one or two decades. In addition, statistical approaches assume the data to be statistically in-dependent (Lesschen et al., 2005)

2.5. Artificial Neural Networks Model

Artificial neural networks (ANNs) were first developed by Rosenblatt (1958), who explained the perceptron by modelling the brain's interconnected system of neurons. ANNs consist of layers and neurons, which simulate the structure of human brains (Fu, 1995). Through computer applications, ANNs have been used in disciplines such as medicine, economics, and mechanical engineering (Aisa et al., 2008; Pijanowski et al., 2002). In the last few years, with advances in computing performance and the increased availability of powerful and flexible software, ANNs have been used in land-use modelling (Almeida et al., 2008; Tayyebi et al., 2011). In terms of predicting land-use change, ANNs have been applied in four phases (Pijanowski et al., 2005). First, data variables are assigned to input units (nodes), with the variable values of land-use change typically observed from historical data. Second, the network is trained using a subset of inputs. Third, the neural network is tested using the full input data set. Fourth, information from the neural network is used to forecast change (Pijanowski et al., 2002). The Land Transformation Model (LTM), which couples ANNs with GIS, was developed in 1995 to forecast land-use change over large regions (Pijanowski et al., 1995). In the LTM, GIS is used to develop the spatial predictor drivers and perform spatial analysis on the results (Pijanowski et al., 2002).

A significant advantage of neural networks is the ability to combine data from different sources into the same classification. This model also has the strength of linking changes in land-use to a variety of socioeconomic, political and environmental factors. ANNs are especially useful for policymakers interested in the optimal configuration of an area based on different policy goals (Eric et al., 2007).

Nevertheless, an ANN is usually treated as a "black-box" with which the weights are uninterpretable due to the presence of hidden layers and the nonlinearity of the activation function. Neural nets are not self-explanatory; there are no standard tests that can measure the degree of variability in the outputs explained by certain inputs or the significance level of the predictions. An ANN with a highly complex architecture and optimum network geometry (e.g. the number of hidden layers and the number of nodes in hidden layers) may perform well with one data set and very poorly with another. Time is required to adequately train and test neural networks. The learning curve is steep, and only developers with experience will become more efficient using this technique (Changhui et al., 1999).

2.6. Agent-based Analysis Model

Land-use change is a complex process that includes actors at different social and spatial levels. Hence, interest in the application of agent-based and multi-agent system tools (human land-use decisions) to model land-use change has increased rapidly (Evans et al., 2004; Filatova et al., 2013; Kelley et al., 2011; Valbuena et al., 2010). An agent may be a land manager, a social organization such as a village assembly or local government body, or even a neighbouring country (Parker et al., 2001). Agents' preferences can be defined by expert judgment or through questionnaires (Lantman et al., 2011).

This method/technique allows modellers to capture the specialized knowledge of stakeholders and, thus, to provide a tool for scenario analysis and knowledge discovery (Fennell, 2013). Matthews et al. (2007) noted that agent-based analysis complements other techniques. However, the nature of analysis in agent-based models means that some important detail is lost. These models tend to concentrate on the most readily apparent and easily quantifiable aspects of land use, without accounting for such factors, outmigration, changes in techniques and input use, and the influence of regional and global economic variables.

2.7. System Dynamic Model

System Dynamic (SD) is a simulation technique originally proposed by Jay W. Forrester in the 1950s to achieve systems thinking in solving complicated management problems. The SD modelling technique uses stock flows and feedback loops to understand how physical processes, information

flows and managerial policies interact to create dynamic variables of interest (Liu et al., 2013), and to search for alternative policies (Costanza et al., 1993).

In 1972, Meadows used the SD theory to develop Limit to Growth models to assess the impact of pollution, population growth and resource use, including that of land (Donella H. et al., 1972). Voinov et al. (1999) designed the Patuxent Landscape Model, a SD model, to simulate fundamental ecological processes: the model interacts with a component that predicts land-use patterns for the Patuxent watershed in the United States. A well-known SD in land-use research is SALU, a model of land-use change for the Sudano-sahelian countries of Africa. The SALU model reflects the expansion of agricultural land, a process driven by demand. The model works on the basis of a ranking that accounts for climatic, physical and economic factors (N. Stephenne, 2001).

The Economic Systems Land Use Management System Dynamics Model (SLUMSD) is also based on the conceptual dynamics framework (Yu et al., 2003). Systems thinking is used to develop dynamics of sustainable land-use management in a river basin, with consideration given to human activities and land, water and air resources. Results show that the SLUMSD model can help those responsible for land-use management decisions. Shen et al. (2009) developed a SD model for sustainable land-use planning and development in Hong Kong, while Yu et al. (2011) modelled land-use change in Daqing City, China.

The land-use process is never static. It changes constantly in response to the dynamic interaction between drivers and the feedback to these drivers from land-use change (Lambin et al., 2003). Compared with statistical frameworks, SD models try to simulate temporal changes in the land-use process in order to address the interactions between processes and driving factors in different scenarios. The models can capture the effects of new land-use policies and, through the incorporation of different factors, predict future uses of the land. As the model is not spatially explicit and predicts only aggregated values of land-use change, hence The major weakness of SD is the lack of sufficient spatial analytical capabilities (Costanza, 1990; N. Stephenne, 2001; Stéphenne et al., 2001).

3. METHODOLOGICAL INTEGRATION IN LAND-USE CHANGE MODELS

Capturing the complexity of land-use change is one of the most important issues in land-use change modelling (Ronneberger et al., 2009). As each single research methodology is a part of a broader context, no single model captures all the characteristics of land-use change (Castella et al., 2007; Van Duivenbooden et al., 1998; Verburg et al., 2001). In light of that, the integrated approach, including methodological integration aspect, has emerged as the most promising approach for reconciling the complexity and dynamics of land-use change (Lambin, 1994; Rounsevell et al., 2012), projecting alternative pathways into the future, and conducting experiments that test our understanding (Veldkamp et al., 2001). Combining the best aspects of different methods/techniques helps cover various disciplines (Eric et al., 2007), mutual relationships and link social science with geographical data to represent the processes driving changes to land systems and land allocation (Breuer et al., 2006; Subedi et al., 2013).

The dimension of methodological integration is not the same in different models. Michetti (2012) divided the link within models into off-line runs (the output of one model used as the input to a second model), soft-link (the same process as off-line runs but accounts for feedback effects and model integration until simultaneous convergence between the two models is reached) and hard-link (uses a reduced-form model, more detailed and more aggregated; assures long trend and consistent dynamics with immediate feedback) based on different degrees of coupling complexity. Heistermann et al. (2006) reviewed a combination of geographic and economic techniques, but their review did not cover all the integration combinations involved in land-use models. The large diversity in methodological integration that has evolved over recent years has prompted the authors to assess the overall picture. In this section, we detail various methods of methodological integration employed

Table 1. The methodological integration within land-use change models

No	Type of integration	Operational model	Non-operational model
1	Economic and statistical based models	KLUM-GTAP (Ronneberger et al., 2009); CLUE-GTAP (Britz et al., 2011); MAGNET – CLUE (Rutten et al., 2014)	
2	Economic based models and Cellular Automata	IMAGE- GTAPEM (Letourneau et al., 2012; Strengers et al., 2004)	
3	Markov Chains and Cellular Automata	IDRISI Paegelow et al. (2008) Poska et al. (2008), Thapa et al. (2011), Adhikari et al. (2012), and Kityuttachai et al. (2013) Dinamica EGO(Mas et al., 2014; Thapa et al., 2011)	Bura et al.(1997); Jenerette et al. (2001); Housset et al. (2006), Sun et al. (2007); Fan et al. (2008), Kamusoko et al (2009); Mitsova et al. (2011); Guan et al (2011); Zhang et al.(2011); Sang et al. (2011); Zhou et al. (2012), Chen et al. (2013); Subedi et al.(2013);
	Markov Chains and Cellular Automata, Statistic		Peterson et al. (2009), Lei et al. (2012) and Jokar Arsanjani et al. (2013)
4	Artificial neural networks and Cellular Automata		Pijanowski et al. (2005); Charif et al.(2012); Lee et al. (2013); Ding et al.(2013)
5	Agent based and Cellular Automata	CORMAS (Le Page et al., 2000), and LUPAS (Landuse planning and analysis system) (Roetter et al., 2005; Van Paassen et al., 2007); SWARM (Perez et al., 2012; Schaldach et al., 2011); ASCAPE (Eeftens et al., 2012).	Parker et al. (2003)
	Agent based and Cellular Automata, statistic	ABMs and CLUE Castella et al. (2007)	Filatova et al (2013)
6	System Dynamic and Cellular Automata	LUMOS (de Nijs et al., 2004; Geertman et al., 2007). LUSD He et al. (2005)	Carneiro et al. (2004); Deal et al. (2004), Shen et al. (2007), Gharib (2008); Han et al. (2009); and Lauf et al. (2012).
7	System Dynamic and statistical analysis	CLUE and the GAMS-based Village Farm Household Model (VFHM) (Gibreel et al., 2014)	Zhan et al. (2007); Luo et al. (2010) and Zheng et al. (2012).

in land-use models, both operational and non-operational. The methodological integration within land-use change models is presented in Table 1.

3.1. Economic and Statistical based Models

Most economic models are developed without spatial determinants, which limits their ability to answer “where” questions (Verburg et al., 2006). Hence, economic models cannot link land-use demand with the impact on land-use systems. More recent work in land-use modelling has focused on furthering integration between economic based models and statistical techniques. Economic theory is used to analyse market and policy factors in order to quantify demand for and supply of land-intensive commodities, while statistical analysis is used with regard to the allocation of land-use types (Heistermann et al., 2006).

Of those models which integrate economic and statistical methods, CLUE-GTAP (Britz et al., 2011) combines two independent models – CLUE and GTAP. Global Trade and Analysis (GTAP) – the economic based model – is used to calculate changes in land-use demand. The standard GTAP model is characterized by an input–output structure based on regional and national input–output tables (Verburg et al., 2008). The most important inputs of the GTAP model are the demographic, macroeconomic and technological developments and policy assumptions. The GTAP model calculates changes in land demand by maximizing a profit function for a representative producer for each sector of a country or region (van Meijl et al., 2006). CLUE uses logistic regressions to identify location suitability and simulate the competition and interactions between different land-use types (Verburg et al., 2008). In other word, CLUE was used to translate these demands to land use patterns

KLUM-GTAP (Ronneberger et al., 2009) operates similarly. KLUM and GTAP-EFL is employed to assess the integrated effects of climate change on global cropland allocation, and the implications climate change poses for economic development. The GTAP-EFL model, an extended version of the Global Trade Analysis Project model, determines regional demand for crops and pasture. The Kleines Land Use Model (KLUM) is a scale-independent global agricultural land-allocation model. The land-use choice module chooses the set of alternatives with the highest utility by means of logistic regression, with the resulting allocation grid based. Allocation decisions are not based on allocation rules which aim to satisfy a defined demand, but on a dynamic allocation algorithm, which is driven by profit maximization under the assumption of risk aversion and decreasing returns to scale. This means that land allocation under the KLUM model is firmly based on economics and that the validity of long-term predictions is ensured.

A recent example of an economic-statistical model is the combination of Modular Applied GeNeral Equilibrium Tool (MAGNET), a global economic simulation model, with the model CLUE (Rutten et al., 2014). MAGNET is based on GTAP. The main output of MAGNET is a set of economic indicators that cover economic change, sector growth, employment, food consumption, prices and trade. Based on assumptions of economic growth and development, MAGNET also determines the demand for land. MAGNET is unable to show the spatial dynamics of land-use change, an output that is covered by CLUE.

3.2. Economic based Models and Cellular Automata

The Integrated Model to Assess the Global Environment (IMAGE) (Letourneau et al., 2012; Strengers et al., 2004) combines different sub-models adopted from a wide range of disciplines. The land-cover sub-model, an allocation tool based on CA, allocates the commodity demands. Land demand is calculated according to land potential by the Agri-cultural Economy Model. However, the economic demand module is theoretically weak as trade and market interactions are not dynamically represented. The Europe’s rural areas (EURURALIS) project aims to improve this weakness by coupling the IMAGE model to GTAPEM (a GTAP model that draws on the Organization for Economic Cooperation and Development (OECD) Policy Evaluation Model (PEM), a version of the standard GTAP model, to calculate production of food and animal products. A management factor is also incorporated. IMAGE allocates land to satisfy a given demand using land productivities that are updated by management-induced yield changes as determined by GTAP. The advantage of coupling the two comprehensive models lies in the production of a detailed and comprehensive picture. However, there is a risk of redundancies and inconsistencies given that some processes, such as the allocation of land, are covered in both models.

3.3. Markov Chains and Cellular Automata

The simplest Markov Chains modelling method is purely non-spatial; only cell states are considered and no attention is paid to the influence of neighbour cells. In order to take account of neighbouring states and spatial allocation in the modelling process, Markov Chains and CA are combined. The Markov Chains process, based on transition matrices, controls temporal change among land-use types, while

CA models, using local rules that consider neighbourhood configuration and transition potential maps, control spatial pattern change (Pontius et al., 2005). In this combination, spatially-explicit transition probabilities of land-use change depend on land location and neighbourhood influences. Mitsova et al. (2011) summarized the five steps of the Markov Chains – CA model (Markov-CA): (1) a Markov Chains transition matrix establishes the transition frequency of each cell within a specific land-use class; (2) multi-criteria evaluations determine the suitability and location of transitioning cells with CA; (3) numbers of iterations are assigned; (4) scenarios are developed; (5) model validation.

The Markov-CA model is reinforced by GIS, which helps to minimize difficulties in data processing and the limitation of spatial resolution. GIS is used to define initial conditions, assign parameters to the Markov-CA model, calculate transition matrixes, and determine neighbourhood rules (Kamusoko et al., 2009). GIS based Markov-CA models are proven to model land-use change with a high degree of accuracy (Guan et al., 2011; Subedi et al., 2013), especially with regard to urban growth projection (Mitsova et al., 2011; Zhang et al., 2011), and have been applied widely: Jenerette et al. (2001), Bura et al. (1997), Housset et al. (2006), Sun et al. (2007), Fan et al. (2008), Kamusoko et al. (2009), Sang et al. (2011), Zhou et al. (2012), Chen et al. (2013). The Markov-CA model is the foundation of the Integrated GIS and Remote Sensing Software Developed (IDRISI) program, which was employed by Paegelow et al. (2008), Poska et al. (2008), Thapa et al. (2011), Adhikari et al. (2012), and Kityuttachai et al. (2013). Another Markov-CA model is Dinamica EGO (Environment for Geo-processing Objects), which simulates landscape dynamics using Markov Chains to determine the quantity of change and the CA approach to the reproduction of spatial patterns (Mas et al., 2014; Thapa et al., 2011).

In order to develop a more efficient hybrid model, Peterson et al. (2009), Lei et al. (2012) and Jokar Arsanjani et al. (2013), combined logistic regression with the Markov-CA model. In this model, logistic regression was utilized to create a probability surface and to determine the most probable sites for development, while Markov Chains were used to measure/calculate change. CA is a tool which allocates probable changes under predefined conditional rules. The hybrid Statistical analysis-Markov-CA model has been shown to offer certain advantages compared with traditional analysis techniques.

3.4. Artificial Neural Networks and Cellular Automata

ANNs have recently been included in the domain of CA simulations. The ANNs-CA model can help to overcome the problem of transition rules in a single CA method (Li et al., 2002). When multiple land-use categories are presented, the transition rules of CA models become substantially more complicated as the simulation involves the use of a much larger set of spatial variables and parameters.

The ANNs-CA model determines the transition probabilities of multiple land-use categories by using multiple output neurons under the ANNs concept. The model copes with the complex relationships between variables because ANNs have non-linear mapping abilities that deal with poor and wrong data. This integration is especially useful where the simulation of complex systems involves many parameters, as is the case with land-use systems (Charif et al., 2012; Ding et al., 2013; Lee et al., 2013; Pijanowski et al., 2005).

3.5. Agent based and Cellular Automata

Agent-based methods are combined with CA modules to form Agent-based Models (ABMs). Agent-based methods use rules that define the relationship between agents and their environment and determine the sequencing of actions in the model. CA modules represent the landscape under study, including a variety of spatial processes and influences relevant to land-use change (Parker et al., 2003). By combining agent-based techniques with spatial models and linking the behaviour of individuals to the behaviour of groups, scale dependencies can be explored in detail. These models are useful for representing cross-scale interactions and feedbacks, bottom-up and top-down, as agents are associated with a location in geometrical space (Berger, 2001). The involvement of agents also makes

it possible to simulate emergent properties that may exert a significant influence on the behaviour of systems in the longer term. This is not a feature of most mono-discipline models.

Parker et al. (2003) simulated the evolution of a system of settlements by integrating CA with an agent-based approach. One of the most influential ABM models is Swarm (Perez et al., 2012; Schaldach et al., 2011). This model has inspired other ABM toolkits such as the Recursive Porous Agent Simulation Toolkit (RePast) (Brown et al., 2005; Xie et al., 2007), Ascape (Eeftens et al., 2012), Common-pool resources and multi-agent systems (Cormas) (Le Page et al., 2000), and the Landuse planning and analysis system (LUPAS) (Roetter et al., 2005; Van Paassen et al., 2007).

ABMs also involve other modelling techniques, including analytical and statistical (Filatova et al., 2013). This can enhance analysis of the processes and patterns of land-use change. To improve estimates of the influence of various drivers of land-use change in a mountain area of Vietnam, Castella et al. (2007) integrated ABM and CLUE.

3.6. System Dynamic and Cellular Automata

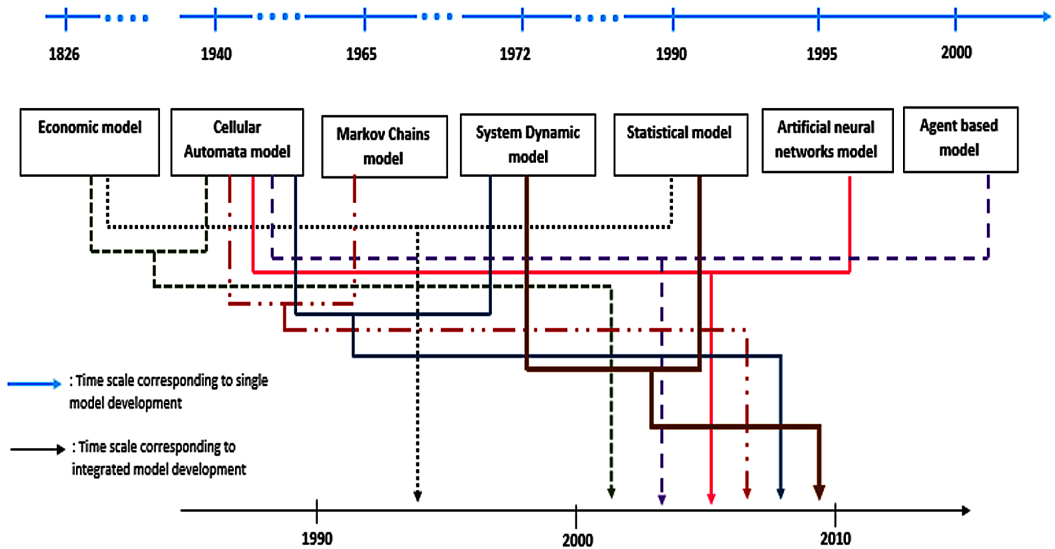
The ability of the SD model to represent the spatial process is weak because it cannot cope with a mass of spatial data and does not describe and model the distribution and situation of spatial factors (Zhang, 1997). At the same time, macro-scale political, economic and cultural driving forces, which exert an important influence on land-use change, are represented poorly by CA, a “bottom-up” model. For this reason, the Dutch National Institute for Public Health and the Environment (RIVM) developed the Environment Explorer (part of LUMOS, the Land Use Modelling System toolbox managed by the Netherlands Environmental Assessment Agency). This model is structured and operated on three spatial levels. At the national level, SD is used to determine the area of land needed for residential, commercial, industrial and recreational use. This is done by analysing the interaction of six main economic sectors: agriculture, glasshouses, industry, commerce, service and recreation. At the regional level, a spatial interaction technique is employed to model the localization of land-use demand, with the Netherlands subdivided into forty regions. A calculation is made to determine the type and extent of land-use, measured in hectares, in each region. At the local level, CA provides for a dynamic allocation of regional spatial claims within a grid of cells. This micro-model calculates transition potentials at the local scale for each step in time (one year), cell, and type of land use (de Nijs et al., 2004; Geertman et al., 2007).

He et al. (2005) developed the Land-use Scenario Dynamics model (LUSD), which integrates SD models and CA to predict changes to land-use in China over the next 50 years. The basic premise of LUSD is to use SD models to model land-use demand at the regional and national levels, then to allocate land use at a local level. Consideration is given to land-use suitability, inheritance, and the neighborhood effects of the CA model in balancing land-use demand and supply. The application of LUSD in China suggests that the model reflects the complex behaviours of various land-use systems, to some extent at least, and is a useful tool, through the integration of “bottom-up” CA models and “top-down” SD models, for assessing the potential impact of land-use on ecosystems. Han et al. (2009) devised an integrated SD-CA model for urban growth research in Shanghai. They found that the model proved competent in monitoring and projecting the dynamics of urban growth. Other studies that follow the same framework include those of Carneiro et al. (2004), Deal et al. (2004), Shen et al. (2007), Gharib (2008) and Lauf et al. (2012).

3.7. System Dynamic and Statistical Analysis

Zhan et al. (2007), Luo et al. (2010) and Zheng et al. (2012) describe an integrated methodology in which the CLUE model is combined with a SD model to analyze land-use dynamics. The SD model covers the temporal heterogeneity of fundamental changes in macro-economics, demographics and technology, and those changes to economic policy that influence land-use demand and supply in specific regions. The CLUE model simulates land-use change, with consideration given to land-use suitability, spatial policies and the restrictions that satisfy the balance between land-use demand

Figure 1. Relative timing: the development of methodological integration in land-use change models



and supply. This SD-CLUE combination is able to reflect the complex behavior of land-use systems at different levels, to some degree at least, and is a useful means by which to analyze the complex factors that drive changes to land-use (Luo et al., 2010). Recently, an integrated model was developed (Gibreel et al., (2014) that combines CLUE and the GAMS-based Village Farm Household Model (VFHM), which is SD based. Given a set of goals and constraints, this model can determine the optimal allocation of land, labor and capital. CLUE was used to simulate land-use change based on empirically quantified relations, with logistic regression employed to establish the relationship between land use and the factors that drive change (Gibreel et al., 2014).

4. DISCUSSION

In this part of the paper we discuss the achievements of methodological integration in land-use change models, together with the challenges, and analyse future trends with reference to the spatial and temporal dimensions of land-use systems.

4.1. Achievement of Methodological Integration in Land-use Change Models

Methodological integration achievements made include (1) solving of problems of temporal and spatial scale, and (2) covering a multi-discipline and multi-scale approach.

4.1.1. Solving Problems of Temporal and Spatial Mismatches

Methodological integration can help resolve spatial and temporal mismatches in different ways. The involvement of agent-based within a complete model linking households with policy making process can help reduce the temporal gap in the policy making process (Rindfuss et al., 2004). Spatial regression techniques have solved spatial scale mismatches between the artificial imposition of rectangular boundaries on grid cells and behavioural decision-making units (Munroe et al., 2007). Combining an agent-based and spatial regression techniques with other modelling method/techniques, therefore, can help solve spatial and temporal mismatch problems.

4.1.2. Cover of Multi-discipline and Multi Scale Approach

Each method/technique works to a certain scale; combining two or more methods/techniques is the key to addressing the multi-spatiotemporal scale characteristics of land-use systems (Rindfuss et al., 2004; Verburg et al., 2004). Methodological integration helps link macro-level analysis with micro-level dynamics to cover multiple aspects of complex land systems, giving such models an advantage over traditional approaches (Erb et al., 2013; Lambin et al., 2006). Multi-scale analysis can be obtained by combining rule-based/SD models or economic models with one of the following models: Markov Chains, statistical models, CA and ANNs. SD and economic models are used for estimating land demand and considering driving forces (mostly macro-economic and demographic factors, as well as social, accessibility and climate variables) on a broad scale – typically at the level of administrative spatial units. Markov Chains, statistical models, CA and ANNs are used to explain land allocation, typically at a polygon or pixel micro level, and the underlying process that leads to different land-use patterns and change based on biophysical drivers such as soil type, water level and distance to roads. The integrated approach also supports models that operate on a global scale. There is a need for more land-use projections on this scale, especially with regard to climate change issues and environmental impact assessments of land-use change. Many important drivers and consequences of land-use change are global – international trade shifts, land requirements in different world regions, and competition for water resources (B. L. Turner, 2009).

Temporal complexity in land-use models can be dealt with through integration with SD models. This allows for accurate representation of rapid time changes (a day or a month, for example) in a land-use change system (Tews et al., 2006; Wang et al., 2012).

4.2. Limitations of Methodological Integration in Land-use Change Models

In theory, more complex models should perform better than simple ones. Although methodological integration allows more variables, space time patterns and social-biophysical processes included in models, potential drawbacks must be taken into account. The representation of sophisticated mechanisms, such as feedback loops and cross-scale interactions is a time-consuming task (Rotmans et al., 2001). Time is needed to amplify a huge amount of data and to find and become familiar with the knowledge required to cover the multidisciplinary characteristics of the land-use process. Higher level of integration requires more data. While many global datasets are now available, a data gap (inconsistent data collection and a lack of sharing frameworks) remains, particularly with regards to developing countries. The process of data integration can be particularly difficult when data sources, units of analysis, spatial extent and spatial-temporal time resolution do not coincide. Furthermore, the absence of a standard classification of land-tenure systems causes difficulty in combining data from different sources (Rotmans et al., 2001).

Methodological integration or combining different techniques requires a wide knowledge of appropriate tools. A lack of knowledge about observations and measurements and the possibilities of conflicting evidence may generate a subjective model biased towards the field in which the modeller works. Researchers from the social sciences may tend to add complexity to the social aspect of the model, while generalizing about its biophysical components. Researchers in the natural sciences may do the opposite. This causes the imbalance in representing the interactions of social, economic, environmental and institutional subsystems (Melillo et al., 2014). Here the question fuels the argument that small and transparent models may be superior to large, complicated models. More knowledge and information does not necessarily mean less uncertainty, and vice versa. The higher the level of integration, the more sources of uncertainty. To solve this issue, error propagation analysis is included in many recent models (Klein Goldewijk et al., 2013).

4.3. Future Trends of Methodological Integration in Land-use Change Models

Our review has identified three main trends in the development of methodological integration. Firstly, it is the systematic feature (Briassoulis, 2000; Gharib, 2008; Hartt, 2011; Milne et al., 2009; Pfaffenbichler et al., 2010). Land-use change is a dynamic and non-linear process. In order to model and better understand non-linear dynamic systems, their main components and interactions must be described. The system approach examines land-use change as one component of a socio-ecological system. Once a system model has been constructed, ‘what-if’ scenarios can be explored more easily than is the case with non-system models (Agarwal et al., 2002). Systematic linking of socio-economic and biophysical drivers and trajectories is needed in order to better understand the thresholds of land use change. This is particularly crucial for assessing future scenarios and the relative impacts of different policy choices.

The second trend is broader boundaries in land-use change models as the method from different disciplines can be combined with each other (Barson et al., 2004; Salvati et al., 2013). Land is used interacts with climate change to affect human communities and ecosystems. At the same time, climate change directly affects where humans live and how they use land (Melillo et al., 2014). Calculating the land-atmosphere exchange in global climate models and predicting the impact of the climate on patterns of land-use are essential components of comprehensive models. In turn, the use of land is linked to options for reducing the speed and extent of climate change, such as expanding forests to accelerate removal of carbon from the atmosphere, modifying the way cities are built and organized to reduce energy and motor transport demands, or altering agricultural management practices to increase carbon storage in soil. In the field of energy safety, land-use models consider the problems associated with biofuels to ensure effective and sustainable land-use management (Diogo et al., 2014; Liu et al., 2012). It is essential such matters are considered if comprehensive integrated models are to cover short-term drivers of global land-use change, such as policy, and mid- and long-term drivers such as societies, economies, technologies and the climate.

Finally, methodological integration amplifies transparency within land-use change model. The development of models depends on knowledge from many disciplines: solutions that integrate knowledge from different land-use sectors are needed. By constructing models in a transparent and inclusive manner, decisions about model parameters are more easily justified to policy makers and the wider modelling community, even where such decisions do not lead to immediate technical improvements. Model output is best evaluated by model developers in cooperation with stakeholders, for this approach limits the chance of mistaken interpretations and conclusions. A land change model created through widespread participation can save later on time-consuming experimental work and calibration processes (Hewitt et al., 2014). And given the development of information technology, sharing data and knowledge is fast, cheap and convenient (Paolucci et al., 2012). Rapid developments in web mapping and the use of geographic information has given rise to neogeography, crowdsourcing and open sources, thereby offering science an unprecedented opportunity to extend its findings beyond the laboratory and refereed journals to the general public (Goodchild et al., 2012). In this regard, open modular platforms that combine software tools and economic assessment routines allow for stakeholder involvement (Fürst et al., 2013). A number of governments have embraced new technologies, including smartphone applications and online interfaces, to involve constituents in land-use planning (Goodchild et al., 2012). Crowdsourcing platforms help to visualize the results of land-use change models, and sometimes enclose the land-use modelling function within the platform environment itself, as is the case with Europe’s FuturICT (Bishop et al., 2011). An even more advanced form of user intervention is offered by interactive models of land-use change, where the user interacts continuously with the model by modifying parameters, providing information (on preferences and priorities, for example), and choosing solutions that most closely match the problem under study (Briassoulis, 2000; Paolucci et al., 2012). The system integrates an agent-based model within an interactive visualization environment, provided through a web interface, to facilitate stakeholder learning in the study area (Pooyandeh et al., 2013). Relevant studies in this regard are Pokahr et al. (2007) and Pooyandeh et al (2013). Spatial

web/agent-based models help to enhance decision making in land management, if the perspectives of stakeholders are considered. The participation approach is an increasingly important aspect of producing a fully integrated, calibrated and valid model (Hosseinali et al., 2013; Jiang et al., 2012; Kelley et al., 2011; Ligtenberg et al., 2004; Matthews et al., 2007; van Vliet et al., 2013).

5. CONCLUSION

This review has shown that there are many different combinations of modelling techniques. There is vast potential for researchers to develop models that make significant contributions to land-use change research and sustainable management policy.

Current methodological integration within land-use models highlight the extent of development in this field in recent years. Multi-scale analysis can overcome some of the intrinsic temporal and spatial deficits of the geographic, economic and system dynamic approaches. In particular, comprehensive integrated models take account of agent and stakeholder participation, which helps researchers to link scientific findings and political and social decisions.

It is important to remember, however, that the integration approach has drawbacks. The simultaneous incorporation of many factors into land-use change models is constrained by the quality and character of the assumptions and data. Increasing the level of functional and spatial aggregation may provide a better representation of these underlying processes, but this will come at the expense of computational efficiency and the ability of the user to interpret, comprehend and employ the model's results. Hence, there is a trade-off between the level of disaggregation and the ease with which results can be used.

While current integrated approaches have great potential, more work is required to improve the modelling of land-use dynamics. The new generation of integrated land-use models will benefit from having transparent structures that employ data quality assessment and reporting tools. Standard protocols need to be established to assess the accuracy of land-use and land-cover classifications.

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