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# Spatially explicit simulation of land use/land cover changes: Current coverage and future prospects

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**ABSTRACT**

Land use/land cover (LULC) change models are powerful tools used to understand and explain the causes and effects of LULC dynamics, and scenario-based analyses with these models can support land management and decision-making better. This paper provides a synoptic and selective review of current LULC change models and the novel frameworks that are being used to investigate LULC dynamics. Existing LULC models that explore the interactions between human and the environment can be pattern- or process-based, inductive or deductive, dynamic or static, spatial or non-spatial, and regional or global. This review focuses on the spectrum from pattern- to process-based approaches and compares their strengths, weaknesses, applications, and broad differences. We draw insights from the recent land use change literature and make five suggestions that can support a deeper understanding of land system science by: (1) overcoming the difficulties in comparing and scaling Agent Based Models; (2) capturing interactions of human-environment systems; (3) enhancing the credibility of LULC change modeling; (4) constructing common modeling platforms by coupling data and models, and (5) bridging the associations between LULC change modeling and policy-making. Although considerable progress has been made, theoretical and empirical efforts are still needed to improve our understanding of LULC dynamics and their implications for policy-oriented research. It is crucial to integrate the key elements of research involved in this study (e.g., use of common protocols and online portals, integration of top-down and bottom-up approaches, effective quantification and communication of modeling uncertainties, generalization and simplification of models, increased focus on the theoretical and empirical bases of models, and open comparative research) to bridge the gaps between small-scale process exploration and large-scale representation of LULC patterns, and to use LULC change modeling to inform decision-making.

**Keywords:** land cover; land use; pattern-based model; process-based model; spatially explicit simulation

**Contents**

## 1. Introduction

Land use/land cover (LULC) changes have been identified as the main driving forces of local, regional, and global environmental changes, which have been stressed increasingly in the evaluation of anthropogenic effects on the environment (Verburg et al., 2015). LULC changes are the results of dynamic human-environment interactions in processes operating at differing spatiotemporal scales (Aquilué et al., 2017; NRC, 2014; Verburg and Overmars, 2009).

LULC change models have become useful research tools in land management, exploration of future landscape changes, and ex-ante evaluation of policy proposals because of their capacity to support the analyses of LULC dynamics' causes and outcomes (Schulp et al., 2008; Verburg and Overmars, 2009). These models have played a vital role as computational laboratories for experiments to explore land system behavior, as real-world experiments frequently are not possible (Matthews et al., 2007; Rounsevell et al., 2012b). In addition, LULC models can provide a framework to address and separate the complex suite of biophysical and socioeconomic factors that affect the rate, quantity, extent, and location of land use changes (Verburg et al., 2004). Further, the models can be applied to forecast multiple land use conversions' effects on climate change, carbon cycling, biodiversity, water budgets, and the provision of other critical ecosystem services (Alexander et al., 2017; Aquilué et al., 2017; Lacoste et al., 2015; Verburg et al., 2002); they also can support the analyses of potential land use changes under multiple scenarios and provide insights into planning processes. In summary, LULC change models are helpful and replicable tools that complement observational- and experimental approaches to analyze and characterize LULC dynamics.

A wide array of land use change models is available currently. They can be inductive or deductive, pattern- or agent-based, dynamic or static, spatial or non-spatial, and regional or global (Mas et al., 2014; Overmars et al., 2007; Verburg et al., 2006a). Because of their different characteristics, this paper outlines comprehensively current LULC change models' state, strengths, weaknesses, applications, and frameworks, and makes inferences about the advantages and disadvantages of different approaches. Further, the paper reviews and discusses the current knowledge about LULC change and the way these complex processes are characterized in the models. By doing so, a number of research gaps are identified and accessible paths are proposed for a better understanding of LULC dynamics and effective land management.

In the first section, the current state-of-the-art in LULC change modeling is reviewed and the features that can be used to make broad distinctions between different modeling approaches are discussed. The second compares two representative models. The third introduces three novel frameworks to model LULC changes that have been adapted from existing models. Finally, current research challenges are discussed and a number of areas for future study are proposed, with the goal to provide a wider contribution to the field of LULC research by answering the following questions:

(1) What approaches and frameworks have been used to model LULC changes?

(2) What are these models' strengths and limitations?

(3) What improvements can be made to advance LULC change modeling?

## 2. Land use/land cover (LULC) change modeling

## 2.1 Spectrum of LULC models

Over the past several decades, a large set of LULC change models has been developed to understand LULC dynamics, explore future landscape patterns, and guide land management decisions (Mas et al., 2014; Verburg et al., 2002). According to the classification proposed by National Research Council (NRC, 2014), LULC change modeling approaches can be placed on a spectrum of pattern- to process-based models (**Table 1**). There are two representative types of models along the spectrum: one is oriented strongly towards describing and extrapolating past patterns (**Figure 1**), and the other is designed to represent the environmental and human decision processes that cause changes in patterns (Brown et al., 2013; Chang-Martinez et al., 2015). However, these approaches usually are implemented jointly and iteratively in practice.

The top-down, pattern-focused approach typically is based on satellite images, maps of environmental variables, and census data. These models use an area of land as the analysis unit and describe the relations between LULC changes and influencing factors based on past changes analyses (Verburg et al., 2006a). The bottom-up, process-focused approach, in which the analysis objects are real actors involved in the LULC change processes, is usually based upon household surveys, and has become popular recently in land system science (Castella and Verburg, 2007; Chang-Martinez et al., 2015).

Understanding the model components, data requirements, and functions is essential to improve their applicability for various research and policymaking purposes.

Accordingly, five principal modeling approaches are reviewed here briefly: machine learning and statistical methods, cellular models, sector-based and spatially disaggregated economic models, agent-based models, and hybrid approaches (NRC, 2014). This review is not exhaustive, but focuses on the broad differences between these models to understand the way these approaches can be used most effectively. The first four model categories range from those focused largely on patterns to those focused primarily on LULC change processes, the first two of which highlight land change patterns, while the remaining two are more process-based approaches. Hybrid approaches fall into more than one category because they combine multiple different models in one simulation framework (Matthews et al., 2007). In the following subsections, the modeling practices in each of the five categories are discussed in turn.

### 2.1.1 Machine learning and statistical methods

These methods focus largely on the projection of patterns, and involve approaches designed to address spatial and temporal relations between LULC changes (outputs) and the characteristics of locations where they are most likely to take place, as represented by spatial variables (inputs). The data are used to construct change potential maps that provide an empirical measure of the likelihood of certain land conversions (NRC, 2014). Together with traditional statistical methods, multiple machine learning techniques, including neural networks (NN), genetic algorithms (GA), decision trees (DT), and support vector machines (SVM) have also been applied to parameterize the biophysical and socioeconomic variables considered in land change models. Applications of these approaches cover various fields, such as NN for urban sprawl, intra-urban dynamics and projections for policy-based scenarios (Almeida et al., 2008; Guan et al., 2005; Maithani, 2014), GA for optimized urban land use allocation and rural land reallocation (Haque and Asami, 2014; Uyan et al., 2015; Zhang et al., 2014), and DT and SVM for classification of heterogeneous land cover (Huang et al., 2009; Keshtkar et al., 2017). A comparative analysis of different modeling approaches has shown that SVM achieved greater agreement of predicted changes than DT and NN in three Belgrade municipalities (Samardžić-Petrović et al., 2017). Comparisons between traditional logistic regression and non-parametric neural networks (NN) illustrated that NN provide a better fit between causal variables and land use patterns (Lin et al., 2011). Dinamica EGO, LTM (Land Transformation Model) and LCM (Land Change Modeler) are typical simulation frameworks in which these different modeling methods have been embedded, and detailed comparisons among them are shown in **Table 1**.

2.1.2 Cellular models

Cellular-based models use discrete spatial units, shaped pixels, parcels, or other land units as the basic units of simulation. These models use a series of input data to simulate transitions of LULC based upon a constant rule set or algorithm. Variations in decision-making do not stem from the decision differences of agents acting as land managers, but rather from the attributes of spatial units (NRC, 2014).

The quantity of LULC change is computed (allocated) in a top-down manner or in a bottom-up procedure that calculates transitions at the level of individual units based solely on their neighbors' conditions. Examples of the former type include Environment Explorer, CLUE-S, and the Land Transformation Model (de Nijs et al., 2004; Pijanowski et al., 2002; Verburg et al., 2002), while the SLEUTH model is a typical representative of the latter category (Clarke, 2008; Clarke and Gaydos, 1998). Often, the LULC changes interact with processes on a local scale, so it is appropriate to simulate these interactions by integrating the two allocation algorithms, e.g., Dyna-CLUE (Verburg and Overmars, 2009).

Cellular models have been widely used because of their simplicity, flexibility, and intuitiveness in reflecting spatiotemporal changes in land use patterns. Traditional cellular models have been adapted and combined with other modeling approaches to improve their availability and performance in solving land system problems. Markov chains and logistic regression have been employed to calculate the quantity of future land changes, and the spatial patterns have been determined by cellular models (Al-sharif and Pradhan, 2013; Arsanjani et al., 2013; Kamusoko et al., 2009). Novel techniques, such as neural networks and support vector machine outlined in the previous section, have been merged with cellular models to parameterize the various variables and define the transition rules (Almeida et al., 2008; Charif et al., 2017). In addition, allocation sequences and local effects within the neighborhoods are another two critical components and focuses in research on cellular based models. Novel modeling frameworks, e.g., LANDSCAPE (LAND System Cellular Automata model for Potential Effects) and LLUC-CA (Local Land Use Competition Cellular Automata model) were developed to address these issues (Ke et al., 2017; Yang et al., 2016).

2.1.3 Sector-based and spatially disaggregated economic models

Two different economic models are used to describe LULC change as a market process and are distinguished primarily by the scale at which they operate. Sector-based models, which are structural and focused on economic sectors, operate at varying, but more aggregated scales. This type of model treats land as a fixed factor of production and represents supply and demand explicitly as contributors to market equilibria (Golub and Hertel, 2012). Further, sector-based models can be classified by the economic system they represent: one type is general equilibrium models that account for the global economy and interactions among all sectors in the economy (Hertel, 2018; Timilsina and Mevel, 2012); the other is partial equilibrium models that focus on specific sectors, including forestry, agriculture, and energy (NRC, 2014; Sands and Leimbach, 2003). These models have been employed to analyze biofuels' effects on global land use, land use change and resulting carbon emissions, competition between agricultural and forest products, and potential influences of climate change on land productivity (Choi et al., 2011; Steinbuks and Hertel, 2016; Taheripour and Tyner, 2013). Efforts also have been made to combine partial and general equilibrium models to complement each other (Britz and Hertel, 2011).

The spatially disaggregated economic models, either in structural or reduced form, simulate individual decisions at smaller scales, including field, parcel, and neighborhood levels (NRC, 2014). The reduced-form econometric models focus on identifying the causal relations between multiple explanatory factors and the resulting LULC changes (Brown et al., 2013; Chang-Martinez et al., 2015; NRC, 2014). Econometric approaches are often employed to evaluate the effects of variables involved in the spatially disaggregated models (Nelson et al., 2016). Progress has been made in applying this type of model to account for the discrete and continuous land- and input-use decisions of farmers (Antle and Capalbo, 2001), the primary environmental, economic, and policy drivers of land use changes (Fezzi and Bateman, 2011), the dynamics of urban land use changes, and the association between housing and land markets (Magliocca et al., 2011).

### 2.1.4 Agent Based Model

The Agent Based Model (ABM) represents systems that consist of multiple agents and simulate their behaviors, thereby representing complex LULC change processes. Agents refer to diverse and interrelated actors, including land owners, farming households, development firms, cooperatives and collectives, migrant workers, management agencies, policy makers, and others who make decisions or take actions affecting LULC patterns and processes (Brown, 2006; Parker et al., 2003). ABMs are nearly always spatially explicit in land change research context. They simulate the individual actors' decisions and assess the resulting micro-scale system behaviors, including all the interactions among agents and the environment (Couclelis, 2000; NRC, 2014; Valbuena et al., 2008). Applications of ABMs are elaborated in the following section and compared with another representative model.

2.1.5 Hybrid approaches

It is difficult to adequately represent the complexity of land use decision-making and account for the processes underlying LULC changes. The data used in LULC change research ranges from satellite images to surveys of human behaviors, and many others in between. Therefore, it is common to combine the approaches described above to make the best use of the strengths of each and to characterize the multiple facets of LULC change patterns and processes. Hybrid approaches can incorporate different conceptual frameworks, theories, and observations (**Table 2**), allowing modelers to choose suitable simulation procedures according to their practical demands (Chang-Martinez et al., 2015).

**Figure 1**

**Table 1**

**Table 2**

2.2 Comparisons of two representative models (CLUE series models & Agent Based Model)

The CLUE series of models and ABMs are most frequently used in land change simulation research. To illustrate the characteristics of different modeling approaches, the basic attributes of these two types of models are described with an emphasis on their commonalities and differences.

2.2.1 Three generations of CLUE series models

The CLUE series models are among the most commonly used land use models worldwide, and their applications range from small areas to entire continents (website of CLUE series models: see Appendix A). Different versions of CLUE models have been developed to serve various research objectives in environmental modeling and land system science, from its original model (Veldkamp and Fresco, 1996b) to later versions, including CLUE-S (Verburg et al., 2002) and Dyna-CLUE (Verburg and Overmars, 2009).

The CLUE series models includes three versions: (1) The CLUE (Conversion of Land Use and its Effects modeling framework) was designed to simulate land use changes by empirically quantifying the relations between land use patterns and their explanatory variables, and incorporating the dynamic simulation of competitions among different land use types (Overmars et al., 2007; Veldkamp and Fresco, 1996b). CLUE-CH (Conversion of land use and its effects in China) is used to apply the CLUE model framework specifically in China to simulate land use patterns at the country-wide scale (Chen and Verburg, 2000; Verburg et al., 2000; Verburg et al., 1999). CLUE-CR is the application of CLUE in Costa Rica that simulates the influences of changing biophysical and demographical drivers on LULC changes and feedback from LULC to those forces at the local, regional, and national scales (Veldkamp and Fresco, 1996a). (2) Subsequently, the modeling approach was modified to operate at regional scales, resulting in the CLUE-S (Conversion of Land Use and its Effects at Small regional extent). CLUE-S spatially explicitly simulates the land use changes based upon an empirical analysis of land suitability, and integrates land systems' competitions and interactions into a dynamic simulation (Verburg and Veldkamp, 2004). (3) An adapted version, Dyna-CLUE, was developed for certain natural and semi-natural land use types to integrate demand-driven changes in land areas with locally determined transition processes (Verburg and Overmars, 2009). The CLUE-scanner is an implementation of the Dyna-CLUE in DMS software of ObjectVision (Verburg et al., 2011). The principal characteristics of these three versions of CLUE models and two applications are summarized (**Figure 2**), and the detailed procedures of the most popular CLUE-S and the most recent Dyna-CLUE are illustrated (**Figure 3 and 4**).

**Figure 2**

**Figure 3**

**Figure 4**

2.2.2 Agent Based Model: *the "third way" to conduct science*

ABM has been described as the "third way" to conduct science because it is an amalgamation of the inductive and deductive approaches. ABMs are based on a series of explicit assumptions and perceptions of the way the world works, and they use these to generate simulated data that can be analyzed inductively (Matthews et al., 2007). These models integrate the effects of human decisions on land use in a formal, spatially explicit way and consider the social interactions, adaptation, and evolution at multiple levels (Parker et al., 2003). Because of social systems' complexity and the unique features of ABM that increase its specificity with respect to individual case studies, no general framework (analogous to Figure 1 for pattern-based models) has been developed to illustrate, design, test, and assess ABMs (Grimm et al., 2005; Murray-Rust et al., 2011; Tian and Wu, 2008). In this section, we focus on the classification of ABMs and their uses thus far by reviewing a representative set of case studies. The following applications of ABMs in four overlapping topic areas related to LULC changes are discussed: modeling land use patterns; urban simulation and policy analysis; representation of human-environmental relations and feedback loops, and specific applications across the regional and global scales. ABMs have been extensively employed to represent complex socio-ecological systems. Thus, this section does not seek to identify and characterize all ABM applications, but focuses instead on the generic aspects of ABM used in LULC change field.

(1) Modeling land use patterns

Compared to the empirical methods, e.g., transition probabilities, ABMs can provide explicit simulation of human decision-making processes and thereby offer greater insights into the actual processes underpinning land use pattern changes. In addition, spatial and landscape metrics are often used in these studies to quantify the dynamics of landscape structure and configuration. Jepsen et al. (2006) used a spatially explicit ABM related to farmers' field location choices to simulate the land use patterns in Ban Que, Vietnam. Agents in the model act to maximize labor productivity which is based upon potential yield, labor costs, and physical constraints. By using several spatial metrics, the modeling outputs are compared with the observed land cover patterns. The results of baseline scenario showed high levels of spatial clustering and the patterns generated in the slope scenario were analogous to the validation data. Using two landscape metrics and household interview data, Evans et al. (2011) established an ABM in Lomue village, Laos, to simulate smallholders' land use decisions and the resulting landscape dynamics. This model effectively reproduced the general spatial patterns of the village area, and the results also indicated an increased inequality in household income over time as a function of the variable rate of rubber adoption.

(2) Urban simulation and policy analysis

In the policy and decision-making cycle proposed by NRC (2014), ABMs play a critical role in two stages: intervention design and decision & implementation. In the former stage, ABMs are used to explore the land system structure and its internal interactions, and investigate dynamics that might benefit from interventions. In the latter stage, ABMs are used ex ante to assess the possible effects of specific policy scenarios. For example, Li and Liu (2008) integrated ABM, cellular automata (CA), and GIS to develop an exploratory spatial tool to compare various development strategies and assess the potential effects of land use policies in Guangzhou, China, a rapidly sprawling city. GIS was used to provide spatial information and CA was to reflect local interactions of physical variables. Sustainable development strategies were embedded in the simulation by appropriately defining agents' behaviors. Based on the high-resolution cadastral data and representations of the interactions among key stakeholders, the Agent iCity model (Jjumba and Dragićević, 2012) established three urban growth management scenarios derived from different growth policies. They found that relative household incomes and property values are critical causes of urban land use pattern changes because households look for and move to affordable homes in suitable neighborhoods.

Considering the complexity of urban system, ABMs are preferred to solely pattern-based models for their ability to encompass various components and elements in cities, particularly considerations of the government, developers, and residents that can directly influence the land use patterns and social environment. For example, by incorporating multiple agent classes (creative firms and workers and urban government), Liu et al. (2016) presented an ABM that simulated different policy scenarios and the corresponding dynamics of creative firms' spatial distributions. Besides, both reviews and specific case studies were conducted to summarize and advance the development of ABMs in urban residential choices (Huang et al., 2013; Jjumba and Dragićević, 2012). By including the agents' attributes and behaviors, and land-market processes, ABMs can offer comprehensive and relatively realistic visualizations of potential urban land use, which may effectively help policy makers adjust land use plans adaptively at different development stages.

(3) Representation of human-environmental relations and feedback loops

Many of the models focus explicitly on socio-environmental interactions and link heterogeneous agent decisions to multiple biophysical processes. Using ABMs to conduct such coupled research between human and environmental systems is helpful in building a decision support system to inform policy decisions. An et al. (2005) developed an Integrative Model for Simulating Household and Ecosystem Dynamics

(IMSHED) to simulate the effects of rural population growth on the forests and giant panda habitat in China. This study integrated various complex mechanisms to simulate the spatial patterns of panda habitat and explored the influences of socio-economic and demographic conditions. The results suggested that policies that encourage family planning, out-migration, or increased use of electricity would preserve panda habitat to various degrees (Matthews et al., 2007). Inner Mongolia Land Use Dynamic Simulator (IM-LUDAS) developed for a semi-arid region in northeast China consists of heterogeneous socio-ecological components and feedback at multiple scales (Miyasaka et al., 2017). The study showed that tree plantations expanded under the SLCP (Sloping Land Conversion Program), accelerated vegetation and soil restoration and household changes towards off-farm economies. However, the livelihood changes were not sufficiently large to compensate for the reduced income resulting from policy-induced reduction in cropland, which provided a new focus for future ecological restoration strategies.

Figure 5 summarizes the major components of human and environmental systems that illustrate the associations and interplays between them through the modeling approach addressed in this subsection (Valbuena et al., 2008; Valbuena et al., 2010; Veldkamp and Lambin, 2001; Verburg, 2006; Verburg et al., 2006a).

**Figure 5**

(4) Specific applications across the regional and global scales

ABMs have been proposed as powerful tools to investigate LULC changes because of the flexible and context-dependent way in which they represent human decision-making (An, 2012; Matthews et al., 2007; Parker et al., 2003). However, because of the inherent complexity of LULC change processes, high data requirements, and diverse decision-making processes, many applications of ABMs have been limited to local scales (Le et al., 2008; Miyasaka et al., 2017), although preliminary attempts have been made to apply it to larger scales (Fontaine and Rounsevell, 2009). Valbuena et al. (2008) constructed an agent topology and allocated agents to multiple categories for a regional analysis that sought to simplify and address diverse farming systems and individual decisions. They also proposed a generic conceptual ABM framework that explicitly considered the diversity of decision-making strategies for different LULC change processes over different regions (Valbuena et al., 2010).

Rounsevell et al. (2014) proposed a schematic framework of the primary components of land-climate systems and their respective interplays across actor, regional, and global scales. They suggested that improved representation of the human entity is needed to conceptualize the options to expand LULC change models from the local to global scales. This includes the processes of agent adaptation, learning, and evolution, formalizing the role of governance regimes, and stressing technological innovation and global network connectivity. However, except for this conceptual framework at the global scale and several integrated models (e.g., integrating CGE models with ABM), ABMs remain fragmented and face a tricky obstacle in representing human decision processes at regional and global scales. This may be because of the barriers on data availability, agent attributes in model parameterization, as well as the scaling and aggregation issues for macro-scale applications (Aquilué et al., 2017; Rindfuss et al., 2004; van Delden et al., 2011).

### 2.2.3 Comparisons and combinations of the two complementary paradigms to integrate LULC change patterns and processes

Although initial research has been conducted to investigate the relations between agent behaviors and land use spatial patterns that benefit from novel modeling platforms integrating GIS functions (Guzy et al., 2008; Liu et al., 2016; Yamashita and Hoshino, 2018), most studies have lacked a spatial perspective and focus on processes occurring in specific locations only. This results from using agents as the basic analysis unit, which makes it difficult to relate agent behaviors to actual land areas and adequately characterize spatial behaviors (Rindfuss et al., 2002; Rindfuss et al., 2004). Space and time dimensions are commonly integrated in spatial models of LULC dynamics (Verburg and Veldkamp, 2004). Some studies have suggested that ABMs are not always the best prediction tools for LULC change science (Groeneveld et al., 2017). Nevertheless, such models can advance the knowledge of LULC processes by conducting experiments that investigate different representations of those processes (Rounsevell et al., 2014). By including autonomous and heterogeneous agents, ABMs are able to explicitly cope with the diverse decision-making processes, which is a key limitation of most land use models that typically apply a single response function over the entire study region and assume that human decision-making is a homogeneous process (Valbuena et al., 2008). Because the ABMs can track individual agents' actions and their outcomes, they have an advantage in conveying the model structure and functions to stakeholders (NRC, 2014).

Both pattern-based and process-driven ABMs have their respective strengths and weaknesses (**Table 3**). The first provides insights about the macro-scale variations of influences and responses to changes in markets, prices, investments, policies, and climate adaptation measures, while the second offers more information about agents' responses and adaptations to variable environmental and policy conditions (Rounsevell et al., 2012b). Choices of the appropriate modeling approach depend on the specific study purpose, the process under research, data accessibility, case study characteristics, and the spatiotemporal extent of the model (Couclelis, 2000; Verburg et al., 2006a). Some efforts have been made to integrate the two types of models into a rule-based version of CLUE-S. This can enhance the overall modeling framework by accelerating the collaboration among researchers from different institutions and between researchers and local stakeholders (Castella and Verburg, 2007). Wang (2016) combined the ABM and CLUE-S to investigate the interactions between household land use behaviors at a micro-level and macro agricultural land use patterns in Mizhi County in Shanxi Province, China. This study resulted in important theoretical and practical understanding of the relations between changes in farming households' activities and the characteristics of agricultural land use patterns and processes.

**Table 3**

## 3. Novel frameworks to simulate LULC dynamics

This section describes the development and exploration of novel modeling frameworks as complementary and parallel approaches to the continued development of existing models. This will provide much-needed diversity in innovative methodology from which the next generation of LULC change models is more likely to benefit (NRC, 2014; Rounsevell et al., 2014).

### 3.1 A spatial demand-allocation procedure based on change occurrence and contagion

Aquilué et al. (2017) introduced a novel spatial demand-allocation procedure to simulate LULC dynamics. Their study explicitly addressed two critical phases inherent in land conversions: the occurrence and spread of land change, corresponding to the initiation of new changes ("patch-of-change") and the generation of the final spatial patterns. The allocation procedure used a sorted queue of cells waiting to be changed. The rate of change occurrence, change expansion, and acceleration of change contagion co-determined the sequence of queued cells, and eventually determined the emergence and extent of patches-of-change. By using this allocation procedure, the authors established a generic, spatially explicit land use model, MEDLUC. The model was designed to reproduce the transformations in the Mediterranean region that occur most frequently: urbanization, agriculture conversion, and rural abandonment. The model can simulate multiple land transitions simultaneously and allows land conversions from multiple land use types to a target type. The study addressed the effects of each parameter on the final spatial patterns and acknowledged the time and path dependence issue. Further, the demand-allocation procedure also supports the spatial translation of LULC change scenarios, such as urban development plans, agricultural policies, and land management strategies, according to the regional policies or global trends.

### 3.2 A new LULC Population Dynamics P system model

Fondevilla et al. (2016) proposed a novel LULC Population Dynamics P system model (PDP) that integrates the main LULC change processes, including plant production, grazing, abandonment, and reforestation. The LULC-PDP model is constructed in seven stages: 1) define and limit the proposed objective and focus of the model; 2) describe the LULC processes to be modeled and the interactions between them; 3) obtain the inputs and parameters; 4) describe the sequences of LULC processes; 5) design the main components of the model; 6) graphically represent the configurations implying the LULC-PDP execution cycle; 7) design the computer simulator. The authors constructed and validated the model to predict future LULC changes annually under three scenarios: business as usual, moderate, and strong reduction of land use intensity. The advantages of PDP are that it: (1) can study complex problems related to interplaying agents and processes; (2) can study numerous species and habitats simultaneously; (3) allows large amounts of information, new modules, and processes to be introduced; (4) does not require processes to be sequenced totally; (5) is flexible and can be applied in other research fields. However, it does not involve the spatial allocation of LULC changes as the classic CLUE family of models.

### 3.3 GIS-based spatial allocation of LULC changes

The CLUE family of models allows LULC changes to be visualized more easily, but under greater uncertainties, in that the models do not consider as many key factors as more recent models, such as the PDP (Fondevilla et al., 2016). The SPA-LUCC model (Schirpke et al., 2012) overcomes this limitation with a combination of both integrated visualization functionality and greater LULC model details, thereby supporting more realistic assessments of LULC changes. It is a GIS-based model that spatially allocates land changes to predict the spatial distribution of future LULC scenarios that consider both environmental and socioeconomic driving forces. It is a stochastic allocation model that translates LULC change quantity into spatially explicit land cover distributions. In addition, it includes multiple tools to project future conversion probabilities on a pixel-by-pixel basis, including calculation of the transition metrics and the cost distance to provide necessary inputs on demand. Initially, known historical land cover simulation was used to validate the model before it was applied to generate future LULC maps for the Stubai Valley, Austria, under three socioeconomic scenarios: business as usual, reduction, and diversification of use. There are some problems about the generalizability of this approach because of the complexity associated with the interactions amongst environmental and socioeconomic conditions, high data requirements, and the irreproducible modeling processes and algorithms. However, GIS-based modeling approaches are user-friendly, support spatial data manipulation, and allow easy implementations under many different modeling frameworks.

## 4. Discussion

### 4.1 Difficulties in comparing and scaling ABMs

Great efforts have been made to explore different aspects of agent-based models, including their theoretical foundations, taxonomies, various decision models, scaling, and applications (An, 2012; Groeneveld et al., 2017; Hare and Deadman, 2004; Matthews et al., 2007; Rounsevell et al., 2012a). However, these studies are limited to specific study areas. In part this may be attributable to the difficulties in comparing and contrasting ABMs, deriving from the strong variation in the terminology used by authors to describe the same processes and features. Another reason is the highly diverse ways in which ABMs are conceptualized, constructed, and presented. This makes it difficult to cross-fertilize concepts, ideas, and structures across these models developed by different research communities (An, 2012; Groeneveld et al., 2017).

Another problem arises in scaling ABMs for LULC research. Many LULC ABMs are parameterized with data collected at micro-scales to describe agent attributes and behavior rules (Rounsevell et al., 2012b). Despite numerous case studies, there has been no attempt as yet to connect, assimilate, organize, and synthesize the findings of these local-level studies (Rounsevell et al., 2014). Most ABMs operate at small, simplified, and hypothetical landscapes, because larger regions include more agents and more complex interactions, which restricts the ability to expand the models over larger geographic regions (Verburg et al., 2004). However, the application of ABMs beyond local scales could provide ways to generate model outputs at scales relevant to synoptic land management and policy formulation. Rounsevell et al. (2012a) proposed three ways to apply ABM over larger geographical extents: scaling out, which uses the same model over larger regions by increasing the extent of input data; scaling up, which aggregates model behavior to a higher representational level and changes the represented entities to a higher level of aggregation, and nesting, which uses a multi-model approach to explore the feedback and interactions among agents and processes. Given the paucity of existing research that has applied ABMs above local scales (Rounsevell et al., 2014; Valbuena et al., 2010), there is a clear research gap in developing scalable approaches so that ABMs become mature and amenable both to regional and global applications.

The use of common protocols in standard model description would support the ability to transfer and generalize LULC ABMs. They serve as a benchmark or checklist, similar to ODD and the ABM taxonomy for land and resource management (Bousquet and Le Page, 2004; Grimm et al., 2006; Hare and Deadman, 2004). Thus, this review proposes that general protocols and architectures related to LULC and LULC changes should be established to facilitate comparing and scaling ABMs. Additional progress can be made by using online portals to share and improve access to global environmental and socioeconomic statistics (Rounsevell et al., 2014). Several websites that provide data for LULC change research are listed in Appendix A.

## 4.2 Inadequate capture and representation of human-environment interactions

Because of the complexity of interacting environmental and socioeconomic processes, it is difficult to explore causes and effects, to identify leverage points for targeting management measures, and to assess the potential effectiveness of those measures (Liu et al., 2007; Summers et al., 2015). Thus far, no model can capture all causes of LULC changes, nor is there an all-compassing theory that considers all the driving forces of land systems (Couclelis, 2000; NRC, 2014; Sohl and Claggett, 2013). The focus of both top-down and bottom-up paradigms also cannot fully interpret the complexity of human-environment interactions across multiple levels (Rounsevell et al., 2012b). Figure 5 is a snapshot of the interactions between human and environmental systems that LULC change models represent. These constitute only a small fraction of the complex relations in human-environment systems and are by no means comprehensive. However, the figure provides a relevant summary that can facilitate a deeper understanding of these interactions and support the integration of partial theories. Synthesis studies have shown that relations in the human-environment systems vary across time, space, and organizational units. Further, historical relations can have legacy effects on present and future conditions (Liu et al., 2007). Parker et al. (2008) proposed three ways to link the human-environment interactions in land system: one-way linkage to use natural science models as inputs to social system; a one-way chain with natural system input and output models, and two-way linkage with internal determination of common variables through interactions in socio-natural systems. Although the importance of the third way is always highlighted, current research primarily uses the one-way linkage or one-way chain (Miyasaka et al., 2017). The development of models that allow addressing two-way feedback is still ongoing (Filatova et al., 2013).

Integrating different land use models to construct a multi-model framework provides an alternative way to explore the interactions in human-environment systems thoroughly. This would use the strengths of existing, individual models while overcoming their weaknesses and developing new insights. For example, Bone et al. (2011) proposed a "modeling-in-the-middle" approach that bridges top-down and bottom-up models and found that this leads to negotiated land use patterns that consider all of the individuals' objectives and behaviors. ABMs benefit from top-down approaches that describe the regional context under different scenarios and provide information about land managers' local responses simultaneously (Rounsevell et al., 2012b). Most present top-down models use generalized and universal allocation mechanisms. However, human responses to different scenarios and environmental policies vary considerably under the influences of various regional contexts, cultural history, and other factors, indicating the need to combine the two modeling paradigms (Rounsevell et al., 2012b). Lastly, these integrated modeling approaches are supported further by the increased availability of multi-scale geo-referenced environmental and socioeconomic data that different research groups exchange frequently and may open new ways to fully explore the complex causal relations in human-environment systems.

### 4.3 Enhancing the credibility of LULC change modeling

Several practices can improve LULC change modeling and enhance its credibility, some of which are developed, but not always followed, while others may require more efforts to test and advance. Uncertainties in LULC change modeling, an issue known well, but one on which research progress has been slow, can arise from the input data, parameters, model structure, processes and their interactions, as well as the mathematical and algorithmic representation (NRC, 2014; Prestele et al., 2016). On the historic LULC change reconstruction side, uncertainties can stem from different reconstruction methods and limited data available for historic states. Future model projections lack validation procedures and rely on the underlying scenarios, relating to the likely non-stationarity in processes. A detailed analysis and effective presentation of uncertainty information provides an increased understanding of the land system (Petersen, 2006; Wardekker et al., 2008). There are two important considerations related to uncertainty: quantification and communication. Recent progress includes a spatially explicit assessment of the uncertainties among a set of existing global-scale LULC models to recognize their amount, spatial extent, and locations (Prestele et al., 2016); the exploration of translating macro-scale uncertainties into that in spatial patterns of land change (Verburg et al., 2013), and the identification and quantification of uncertainties in European and global LULC projections (Alexander et al., 2017). The scenario framework provides a tool to communicate uncertainty about future modeled land use, with broad uncertainties presented as differences in the scenario assumptions. Explicit recognition of stationarity assumptions and the exploration of data for evidence of non-stationarity are also important steps in acknowledging and understanding model uncertainties (Brown et al., 2013). The generalization and simplification of models can play a critical role in improving the ability to analyze uncertainties (Sohl and Claggett, 2013). It is also suggested to use a diverse set of modeling methods (multiple rather than complex models) to evaluate LULC changes' potential effects on the environment. Applying multiple models can also help communicate the uncertainties to stakeholders to gain their trust (Sohl and Claggett, 2013). However, further work to quantify the different types of uncertainties and communicate them with stakeholders is needed to address the causes and variations of uncertainties thoroughly, as well as provide more scientifically rigorous and useful modeling applications.

Validation is often difficult and thus is ignored in most LULC change models, which results in a lack of confidence in the modeling results (Rindfuss et al., 2004; Waddell, 2011). Validation refers to comparisons of model outputs and observed patterns, and the match between processes on which modeled locations and land use patterns depend and the real-world processes (Brown et al., 2005; NRC, 2014). In pattern validation, two or more historic land cover maps are needed to calibrate the model and simulate a map at a subsequent time. The simulated map of land use changes is then compared to the reference map of actual changes and the differences are assessed using various indices. The comparison requires three maps: the initial observed map, the observed and simulated maps at the end of simulation. As an alternative to the usual three two-map comparisons, a novel three-dimensional contingency tabulation that compares the three maps simultaneously has been proposed (Pontius et al., 2011). It is more parsimonious and yields richer information on change amount and allocation performance (Moulds et al., 2015; Pontius et al., 2004). Although multiple techniques have been developed for pattern validation, pattern accuracy has been explored only in part, or more typically, is ignored in applications (van Vliet et al., 2016). This may be because of the scarcity of historic data, the large differences in classification of land use maps and resolution of satellite images, as well as poor conceptual and theoretical understanding (Sohl and Claggett, 2013; Verburg et al., 2004). Similar to pattern validation, process validation has received even less attention and remains a challenge because of the potential (and common) existence of unobservable underlying processes, their complex correspondences with the predicted patterns, and the path dependence of themselves (NRC, 2014; van Vliet et al., 2016). Thus far, only rudimentary attempts have been made to address both pattern and process validation. Much work is needed to enhance simulation credibility for scenario analysis and policy formulation, including a continued focus on fitting historical data, more attention on the models' theoretical and empirical basis, open comparative research, peer review of the modeling framework, and justification of the model's suitability for a given context (Petersen, 2006; Pontius et al., 2008; Rindfuss et al., 2008; Sohl and Claggett, 2013). Addressing these issues would considerably alleviate the challenges of model validation.

### 4.4 Common modeling platform: coupled data and models

A general lack of data, published codes, and common modeling platforms make reliable simulation of LULC changes and replication difficult. Large data gaps remain. There is a long way to reach the position where all of the data needed to characterize various LULC change processes are available. For ABMs, with their high input requirements, modeling highly diverse scenarios, decisions, and agents, it is always difficult to acquire sufficient data to establish a well-parameterized model, especially at the individual or household level. Another problem is that the observed LULC change outcomes may not be adequate to validate the model outputs (Verburg et al., 2004). In addition, the land information from interviews and questionnaires provided by those involved in landscape management (farmers or other agents) may not match the agents' actual behaviors or reflect the real-world situation. Moreover, not all actors behave in the same way in all areas. Thus, a detailed sample survey that seeks to capture information over an entire region may not always represent the diverse behaviors and attitudes amongst the population, which results in a mismatch between the survey results and the statistics (Valbuena et al., 2008). These issues further increase the modeling uncertainties and complexities. For cellular models, fine-resolution data for model validation are not always available because of confidentiality concerns, and typically, the periodicity that socioeconomic data lag behind those of natural science (Parker et al., 2003). This suggests a need for a data infrastructure to collate and collect historical data on LULC changes and a wide array of economic, demographic, and policy statistics (**Appendix A**).

Providing model source codes is encouraged whenever possible to support model (and outcome) transparency, and critically, research replicability (Brunsdon, 2016). The SLEUTH model has been accepted and used widely since its development in the 1990s.

One reason for its success is that its code is available freely to download and use, and its framework is relatively straightforward (Sohl and Claggett, 2013). Several researchers have argued for a common programming language that allows model structures and results to be communicated clearly (Parker et al., 2003). In the CLUE-S model, users can run the model only on the platform provided and have to preprocess the inputs and perform the statistical analyses in other software, which is time-consuming and increases the likelihood of user errors. A good solution is the open and extensible framework Moulds et al. (2015) proposed, in which all modeling steps are implemented in the R environment, allowing users to test the source code and adapt it to their own requirements, and thus the developers can share their code, documentations, and datasets in a common format.

Without a general framework to synthesize findings, the knowledge modeling activities yield does not accumulate (Couclelis, 2000; Ostrom, 2009). A possible strategy to address this problem is to develop a common modeling platform that includes several existing modeling implementations, links to data, and makes the code open and accessible. Such a platform would allow modelers to make informed decisions when choosing their models and factors, make LULC change modeling more transparent and transferable, and thereby address some of the challenges in this field.

### 4.5 Relating LULC change modeling to policy

The past decade has witnessed a profound increase in the number of LULC change models and the spectrum of those discussed above can play different roles in the four-stage policy cycle NRC (2014) proposed. However, the application of these models in land use planning and policy formulation has been limited (Couclelis, 2005; Sohl and Claggett, 2013). Models that can serve as decision support systems for direct use by end-users are scarce (Matthews et al., 2007). This paper has discussed the application of ABMs in urban simulation and examinations of policies' potential effects. However, no examples were found in which land use planners or policymakers actually used the modeling results when making their decisions, which is in line with the conclusions of Rounsevell et al. (2012b). The gaps between LULC change modeling and decision-making support can be attributed to the differences in modelers and policymakers' goals, as well as the models' inherent complexity and lack of clarity, transparency, manipulability, and flexibility (except ABMs) (Valbuena et al., 2008). To bridge this gap, Sohl and Claggett (2013) suggested that land use models should provide LULC information and analyses rather than just contain data, with the goal of engaging decision makers with the models and outputs.

There are other approaches that can improve the applications of LULC models in the decision-making process. Focusing on the most important processes for stakeholders and generalizing those that are less important would facilitate the understanding of model functions and outputs, and increase policymakers' acceptance of the models (Parker et al., 2008). In the current modeling paradigm, stakeholders are absent during the construction and development of LULC projections. Greater participation in the simulation that places decision makers (users) in a central role and involves them in the whole modeling process from data acquisition, model design, data analysis to scenario development is encouraged strongly (Petersen, 2006; Rounsevell et al., 2012b). In addition, decision support systems are a good way to link fundamental research and practical applications, for example, LULC modeling. Verstegen et al. (2012) established a Spatial Decision Support System that includes simulation, uncertainty analysis, and visualization to choose the optimal locations where bioenergy crops can be planted without endangering other important land uses and food production. The decision support systems should incorporate a clear description of modeling framework, suitable representation and communication of uncertainties, well defined input and output variables, and the flexibility to meet different user requirements (Sohl and Claggett, 2013). With such systems and user-friendly interfaces, planners can assess different policy scenarios' potential effects by adjusting the model inputs and comparing the resulting spatial graphs. This is helpful for end users without expert knowledge of modeling theory and statistics, and consequently expands the applications of LULC models in decision-making processes.

## 5. Conclusions and future directions

By reviewing and comparing different modeling approaches, this study has identified a number of important research challenges and highlighted several issues that need to be addressed to improve current LULC change modeling. The following five recommendations may fill the key research gaps and stimulate progress in this field:

(1) Developing generic protocols and making use of online data infrastructures provide

opportunities to overcome the difficulties in comparing and scaling ABMs.

(2) A wide array of models (e.g., top-down and bottom-up paradigms) needs to be integrated to use the strengths of existing individual models and support comprehensive analyses of the interactions in human-environment systems.

(3) Further work is needed to quantify different uncertainties and their sources and to communicate these with stakeholders. This would support the validation of model results and realize modeling that is theoretically solid and empirically justified.

(4) Common platforms and frameworks populated with multiple existing models should be established, providing code in an open environment and linking to related data for further LULC research.

(5) Stronger relations between LULC change modeling and policy making can be realized by generalizing and simplifying modeling frameworks, embedding relevant stakeholders in the modeling process, and constructing decision support systems.

This review has not sought to provide a complete list of all LULC change models, but has focused instead on those most commonly used, comparing their strengths, weaknesses, applications, and the broad differences. By doing so, a number of major research gaps have been identified and possible solutions to them proposed. It is hoped that this work presents a critical perspective on the different LULC change modeling approaches, provides a contribution to strengthen the field’s interdisciplinary nature, and suggests a research agenda that indicates a productive path forward.

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**Appendix A.** Suggested websites for LULC change models and related projects & data

**Table A.1**

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**Figures:**

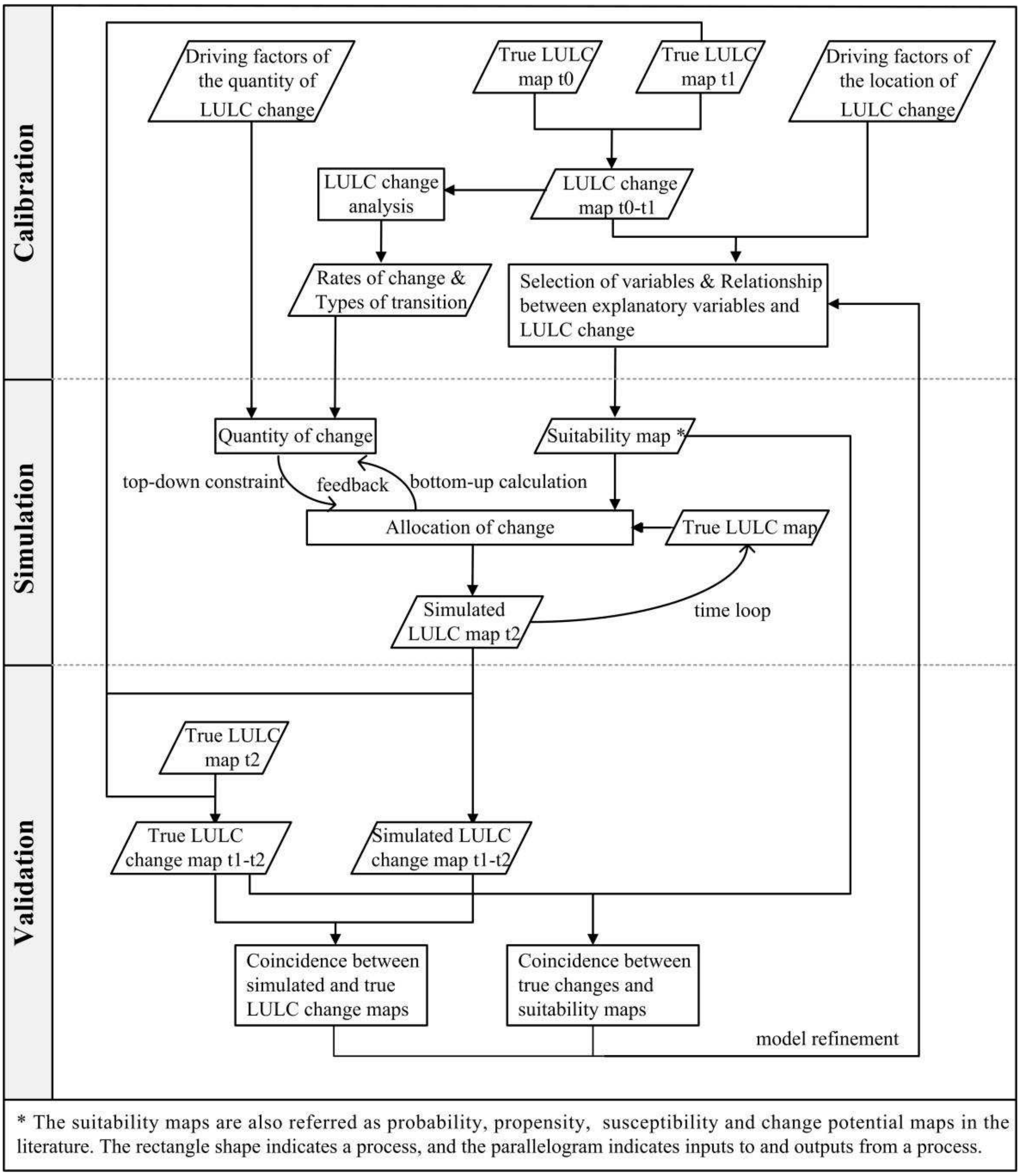



**Figure 1.** Flowchart of the generalized procedures used in spatially explicit pattern-based LULC modeling. Revised from (Mas et al., 2014; Moulds et al., 2015; Verburg et al., 2006a).

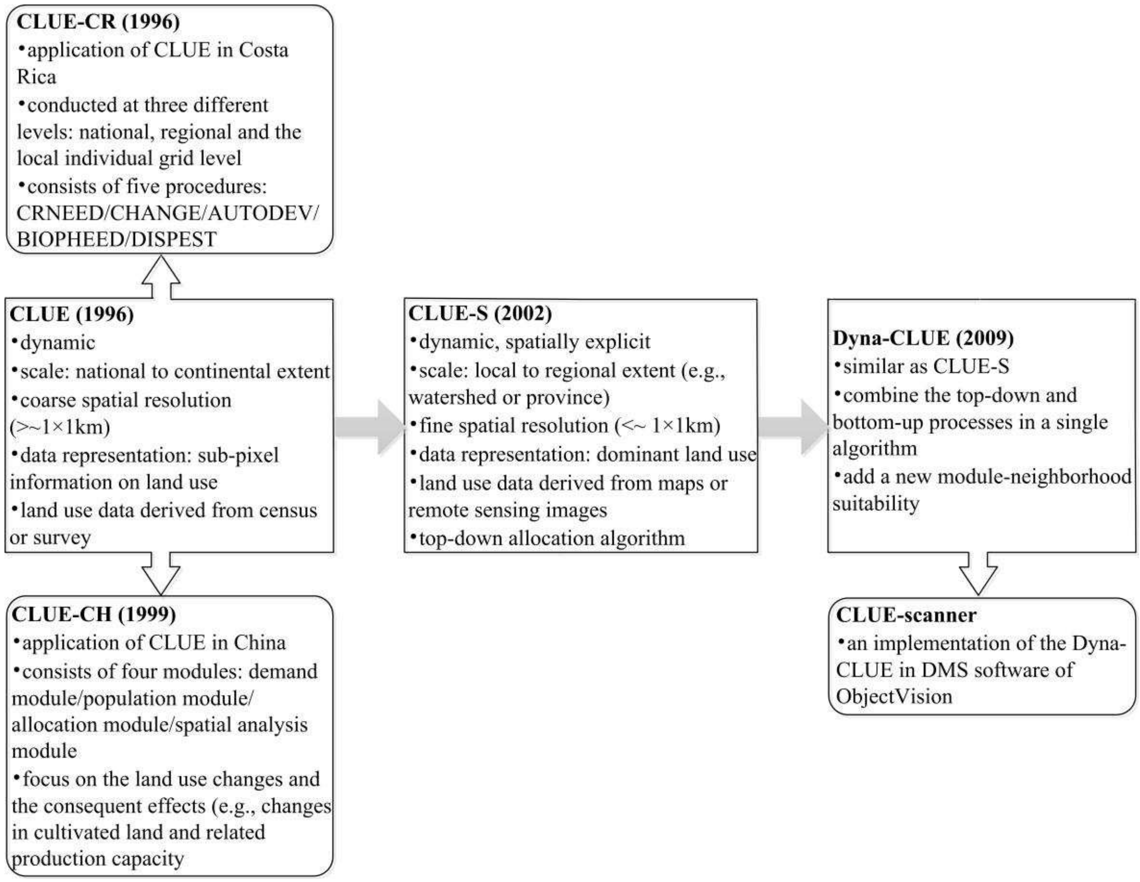



**Figure 2.** Evolution of CLUE series models.

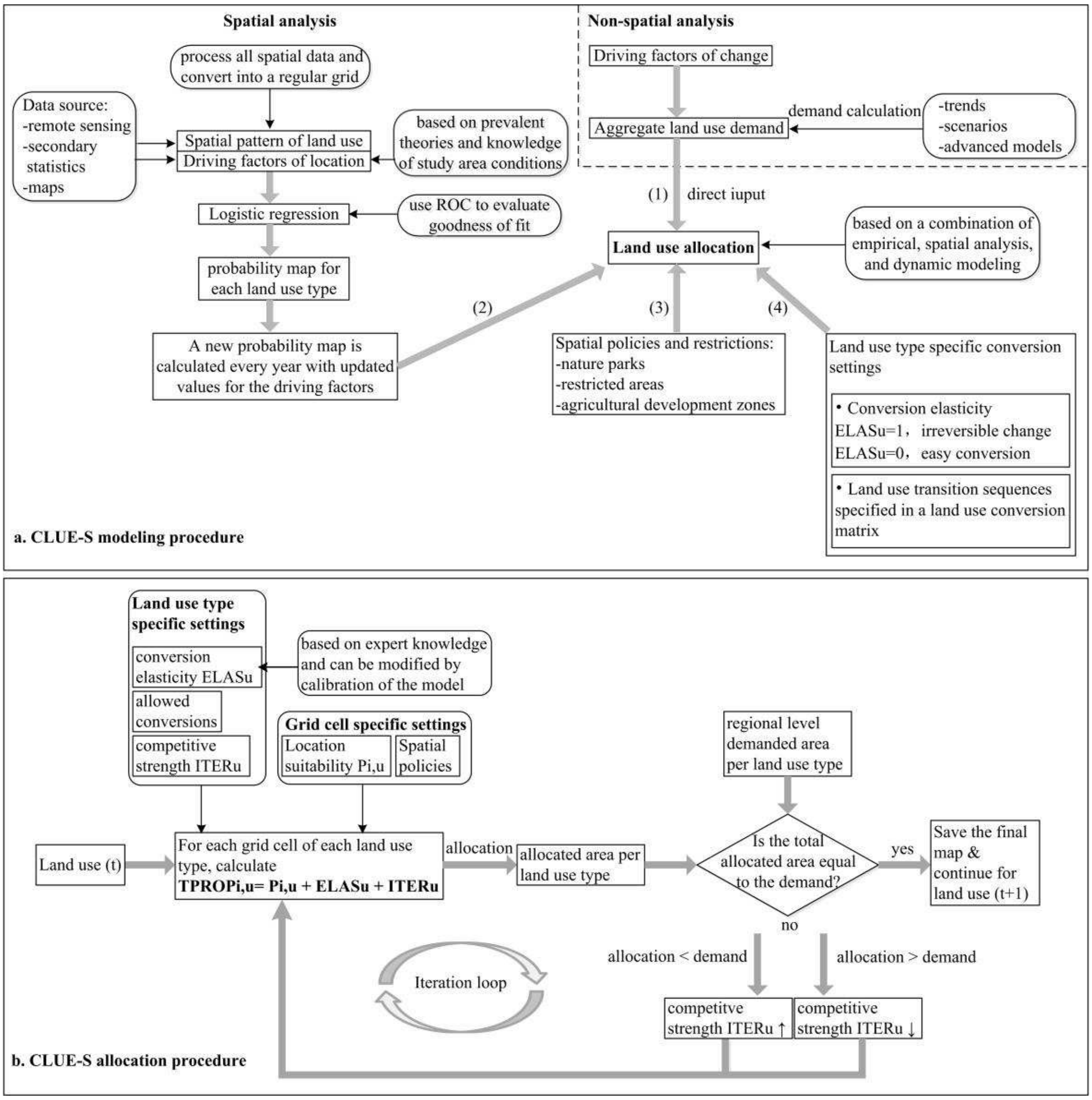



**Figure 3.** Overview of the CLUE-S model structure (Overmars et al., 2007; Verburg et al., 2006b; Verburg et al., 2002; Verburg and Veldkamp, 2004). Thick arrows indicate the main steps of the simulation and thin arrows represent the model parameters and settings. Dotted line in figure 3(a) separates two modules of the CLUE-S model: spatial analysis and non-spatial analysis.

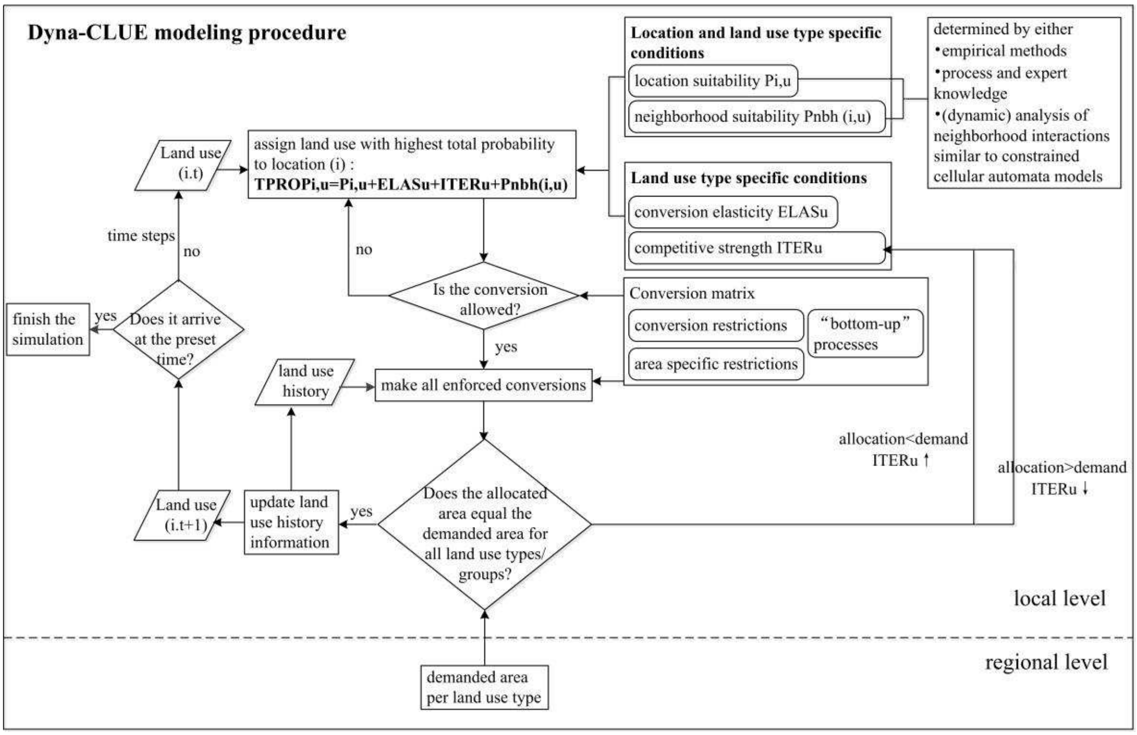
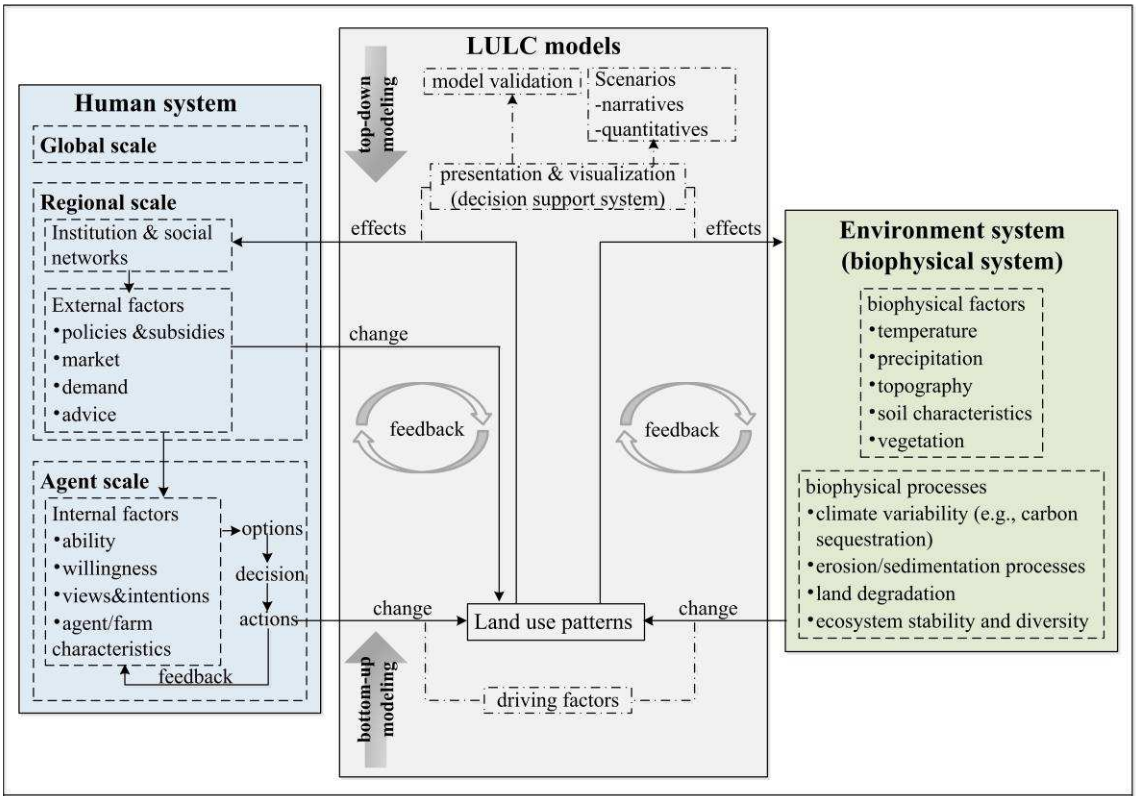



**Figure 4.** Flowchart of the Dyna-CLUE modeling procedures (Verburg and Overmars, 2009; Yan et al., 2016).




Agents' decisions are dependent on the internal and external factors, responding to the internal feedback mechanism that makes agents' s future options based on previous practices, and the external interactions among agents, involving social networks, governmental organizations and the market. Agents' actions can change land use patterns and affect the functioning of landscape and its capacity to provide goods and services. The external factors occur at different organizational levels, including regional and global scales, which can directly influence the LULC patterns of a region and affect agents' ability by establishing certain policies (e.g., subsidies). Land use change models are often used to assess the effects of land change on biophysical factors and processes. Changes in biophysical system can in turn affect the land use patterns, e.g., erosion and sedimentation processes can change the soil depth which will affect the suitability for agricultural activities and the consideration in land use decisions. Besides, we are trying to shedding light upon illustrating the two different modeling paradigms: one is top-down modeling (aforementioned in subsection 2.2.1), which determines the quantity of land use change based on the changes in (global) demand and market conditions; the other is bottom-up modeling, which uses the real actors of land management as analysis objects and focuses on the underlying processes that lead to the resulting spatial patterns.

**Figure 5.** Overview of the potential use of LULC change models to link human-environment systems.

# Tables:

**Table 1.** Generalized characteristics of main LULC change models [1-5].

| Model | Pattern - Process | Key assumptions | Classification criteria | Examples | Strengths | Weaknesses | Application |
|---|---|---|---|---|---|---|---|
| 1.Machine Learning and Statistical Models | Pattern | Strong stationarity | **Statistical approaches:** | | •predict by extrapolating historical patterns<br>•conduct the extrapolation without theory of the detailed processes underlying the changes | •overfitting problem of machine learning<br>•as a "black box", difficult to interpret the model structure and performance of machine learning<br>•lack of causality[7-8]<br>•the weights-of-evidence based Dinamica model did not consider the interactions among variables[9] | •suitable when data related to patterns is available while a lack of theory concerning processes |
| | | | •traditional parametric approaches (logistic regression) | Dinamica model | | | |
| | | | •weights-of-evidence | Dinamica model | | | |
| | | | •markov chains[6] | | | | |
| | | | •generalized linear modeling | | | | |
| | | | •generalized additive modeling | | | | |
| | | | **Machine learning approaches:** | | | | |
| | | | •neural networks | LTM; LCM | | | |
| | | | •genetic algorithms | Dinamica EGO | | | |
| | | | •classification and regression trees | | | | |
| | | | •support vector machine | | | | |
| 2.Cellular Models | | stationarity | •a continuation of historical trends and patterns | | •relatively simple structure and applications<br>•data format matches the land cover data format obtained from satellite images; allows for direct processing<br>•easy parameterization by empirical analyses of time-series data or econometric calibration approaches<br>•flexibility to represent spatiotemporal dynamics | •limited theoretical links between conversion rules and actual decision makers<br>•mostly ignore interplays through societal or other networks<br>•difficult to generalize<br>•usually apply constant algorithms over space and time<br>•ability to reflect the system feedback is limited | •used for various topics (e.g., tropical deforestation, urban growth, biofuel crops, farmland abandonment, and impacts of LULC changes on carbon sequestration) |
| | | | •allocation based on land suitability | CLUE-S | | | |
| | | | •consider the state of neighborhood pixels | CA | | | |
| | | | •CA-based, explicitly simulate urban expansion patterns | SLEUTH | | | |
| | | | •a dynamic CA-based model, comprising three levels (national, regional and grid) [10] | Environment Explorer | | | |
| | | | •simulate one-way transformation from one to another land use type[11] | GEOMOD | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 3.Economic Models | Sector-based approaches | Utility or profit optimisation; general or partial equilibria | Computable general equilibrium (CGE) | FARM; GTAP; EPPA; IMAGE | •address aggregate-level feedback from market interactions or nonmarket feedback that affect the equilibrium<br>•less reliance on the stationarity assumption<br>•improved fidelity on the economic processes leading to land use changes | •PE models require an exogenously given land use sector<br>•CGE models cope with a limited number of geographical regions[12] | •used to quantify the effects of non-marginal changes (e.g., policy changes) to project policy scenario outcomes |
| | | | Partial equilibrium (PE) | ASMGHG; IMPACT; GTM; AgLU; FASOM; GLOBIOM | | | |
| | Spatially-disaggregated approaches | Utility or profit optimisation; | structural | Equilibrium locational-choice models[13-14] | •address the basic role of prices in explaining individual decisions<br>•address the feedback of predicted LULC changes on prices and predict the consequences of policy | •require assumptions on agent behaviors, market structures, and functional forms<br>•limited in the spatial dimension<br>•limited data on revenues and costs | •non-marginal land change prediction and policy scenarios |
| | | | often in reduced form | | •focus on causal identification<br>•impose fewer assumptions on the data | •only suitable for simulating the effects of marginal changes on land change outcomes<br>•limited utilization for modeling landscape changes over longer periods<br>•problems on endogeneity | •used to test multiple specific hypotheses by recognizing key parameters<br>•simulate the land use dynamics corresponding to changes in policies or other variables |
| 4.Agent-Based Models | Process | | exploratory-theoretical models | | •suitable for representing complexity in land systems<br>•able to represent the agent heterogeneity and behaviors, and have various representation forms<br>•easier to communicate the model structure and functions to stakeholders | •limited generalization under other conditions<br>•computational constraints and limited empirical resources | •study the effects of land change process at multiple scales and organizational levels<br>•evaluate projections of LULC or other state variables<br>•model the formation of outcome patterns |
| | | | empirical-predictive models | | | | |
| 5.Hybrid Approach | | | | •Markov-Cellular[15]<br>•Global Land Model[16-17]<br>•Statistical-Cellular-ABM[18] | •use the advantages and reduce some inherent limitations of individual approaches<br>•flexibly match existing theories and approaches to other conditions<br>•facilitate development of new methods<br>•better representation of reality complexity | •increased complexity and difficult causal tracing<br>•difficult calibration and validation | See Table 2 |

Note: LTM (Land Transformation Model), LCM (Land Change Modeler), CA (Cellular Automata), GTAP (Global Trade Analysis Project model), EPPA (Emissions Prediction and Policy Analysis model), GTM (Global Timber Market Model). [1-5]: (Brown et al., 2013; Chang-Martinez et al., 2015; NRC, 2014; Pontius et al., 2008; Pontius et al., 2001), [6]: (Losiri et al., 2016), [7-8]: (Irwin and Geoghegan, 2001; Lambin et al., 2000), [9]: (Mas et al., 2014), [10]: (de Nijs et al., 2004), [11]: (Pontius and Malanson, 2005), [12]: (Rounsevell et al., 2014), [13-14]: (Klaiber and Phaneuf, 2010; Walsh, 2007), [15]: (Guan et al., 2011), [16-17]: (Hurtt et al., 2011; Hurtt et al., 2006), [18]: (An et al., 2005).

**Table 2.** Examples for hybrid approaches to simulate LULC changes

| Hybrid approaches | Goals | References |
|---|---|---|
| (1) machine learning/statistical approaches + cellular model | incorporate land suitability with neighborhood effects to project future land use | (Li and Yeh, 2002; NRC, 2014) |
| (2) sector-based economic model + spatial allocation model | downscale land areas determined in large-scale general equilibrium | (Hurtt et al., 2011; Hurtt et al., 2006) |
| (3) statistical approaches + cellular model + agent-based model | represent the dynamics of both natural and human processes involved in land change | (An et al., 2005) |
| (4) Markov chains + cellular model | determine future quantities of change and the spatial patterns | (Guan et al., 2011) |
| (5) cellular model + agent-based model | MAS (multi-agent system model), represent complex spatial interactions under heterogeneous conditions and model decentralized, autonomous decision making | (Bousquet and Le Page, 2004; Parker et al., 2003) |
| (6) IMAGE + Global Trade Analysis Project model + CLUE-S | study policy effects on agricultural land and Europe’s rural areas | (van Meijl et al., 2006; Verburg et al., 2007) |

**Table 3.** Comparisons of CLUE series models and agent-based model.

| Model | Strengths | Limitations | Application |
|---|---|---|---|
| CLUE-S (Overmars et al., 2007; Verburg et al., 2002) | •explicitly concerns the functions of the whole land use system<br>•simulates multiple land use types simultaneously<br>•can simulate different scenarios<br>•straightforward and easily reproducible regression analysis<br>•relatively easy data collection | •requires knowledge about land use history<br>•limited representation of the relations between variables<br>•does not include the spatial configurations of LULC changes over the historical calibration period<br>•requires external programs | •suitable for various study areas and situations<br>•spatial scenario analysis-useful for natural resource management<br>•simulation of trajectories of LULC change |
| Dyna-CLUE (Verburg and Overmars, 2009; Yan et al., 2016) | •incorporates top-down allocation of land use changes with bottom-up determination of specific land use conversions | •uses empirical and statistical models to represent the land use changes and allocation patterns; however, the relations between land use types and explanatory variables are typically nonlinear in reality<br>•only calculates the neighborhood factors in the initial year, while the impacts of neighborhood will change over time<br>•difficulty in reflecting the influences of emergent policy changes on land use spatial patterns | •useful in situations where it is difficult to determine land use conversions in a top-down paradigm and where local habitat conditions are the most important driving forces of vegetation dynamics |
| Agent-based model (An, 2012; Hare and Deadman, 2004; Li and Liu, 2008; Matthews et al., 2007; Parker et al., 2003) | •flexible specification and design<br>•able to reproduce nonlinear and emergent phenomena based upon individual behaviors<br>•simulates decision-making at different levels, considering the interactions among them and between actors and the environment, and adaptive behaviors<br>•investigates the influences of environmental management policies<br>•integrates social interactions on decision processes and the effects of micro-level decision-making on environmental management<br>•dynamically links social and environmental structures, processes, norms, and institutional factors<br>•explicitly simulates the human decision processes and provides more insights to the actual processes involved in land use change | •limited predictive power at local level<br>•difficult calibration, validation and verification<br>•lack of effective architectures and protocols to represent local actors and their interactions<br>•poor representation of learning processes in real world decision making<br>•extensive and time-consuming data collection | •simulate farming or environmental management decisions<br>•useful to organize knowledge from empirical studies, and explore theoretical facets of land system<br>•land management and policy analysis<br>•participatory modeling<br>•to explain spatial configuration of land use<br>•to test social science concepts<br>•to explain land use functions |

**Table A.1.** Suggested websites for LULC change models and related projects & data

| Models | Suggested websites |
|---|---|
| •CLUE | http://www.ivm.vu.nl/en/Organisation/departments/spatial-analysis-decision-support/Clue/index.aspx |
| •Dyna-CLUE | http://downloads.informer.com/dyna-clue/ |
| •CA | http://www.geosimulation.cn/index_chs.html |
| •Dinamica EGO | http://www.csr.ufmg.br/dinamica/ |
| •ABM | https://www.openabm.org/ & http://ccl.northwestern.edu/netlogo/ |
| •Land Use Scanner | http://www.objectvision.nl/gallery/products/ruimtescanner |
| •Community Earth System Model | http://www.cesm.ucar.edu/ |
| •Community Land Model | http://www.cgd.ucar.edu/tss/clm/ |
| •Open Platform for Urban Simulation | http://www.urbansim.com/ |

| Projects & Data | Suggested websites |
|---|---|
| •NASA ,“Global Land Cover Facility” | http://glcf.umiacs.umd.edu/data/ |
| •European Space Agency & United Nations Food and Agriculture Organization, “GlobCover” | http://due.esrin.esa.int/prjs/prjs68.php |
| •GEON | http://www.geongrid.org |
| •National Science Foundation for the Global Collaboration Engine | http://ecotope.org/projects/globe/ |
| •IPUMS, Terra Populus project | https://www.terrapop.org/ |
| •IPUMS | https://www.ipums.org/ |
| •Geoshare project | https://geoshareproject.org/ |
| •SIMLANDER | https://simlander.wordpress.com/about/ |
| •GEOSHARE | https://mygeohub.org/groups/geoshare |
| •NASA’s socio-economic data centre (SEDAC) | http://sedac.ciesin.org/ |
| •the University of Wisconsin’s SAGE | http://nelson.wisc.edu/sage/ |
| •DataONE | https://www.dataone.org/ |
| •the GLOBE project | http://globe.umbc.edu/ |
| •CCAFS | https://ccafs.cgiar.org/resources/baseline-surveys |