Spatial agent-based models for socio-ecological systems: Challenges and prospects[☆]

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ARTICLE INFO

ABSTRACT

Departing from the comprehensive reviews carried out in the field, we identify the key challenges that agent-based methodology faces when modeling coupled socio-ecological systems. Focusing primarily on the papers presented in this thematic issue, we review progress in spatial agent-based models along the lines of four methodological challenges: (1) design and parameterizing of agent decision models, (2) verification, validation and sensitivity analysis, (3) integration of socio-demographic, ecological, and biophysical models, and (4) spatial representation. Based on this we critically reflect on the future work that is required to make agent-based modeling widely accepted as a tool to support the real world policy.

1. Introduction

The world has witnessed unprecedented changes occurring in coupled socio-ecological systems (SES). Massive irreversible loss of ecosystem services, and global environmental change driven by both socio-economic changes and the adverse consequences of climate change involve cross-scale feedbacks, adaptive dynamics, and interactions between subsystems and their components. It is recognized that these management challenges are best characterized using a complex systems paradigm. Agent-based models (ABMs) have emerged in land and environmental science as a way to better capture complex system characteristics of coupled SES. ABMs for SES have evolved as extensions of other modeling techniques, including analytical and statistical modeling, cellular automata, artificial learning and others. The main added value of ABM as a simulation technique is in its ability to represent behavior of human actors more realistically, accounting for bounded rationality, heterogeneity, interactions, evolutionary learning and out-of

equilibrium dynamics, and to combine this representation with a dynamic heterogenous representation of the spatial environment. ABMs applied to SES almost always operate in a spatial environment as SES are often showing high spatial variations. The spatial component implies that a heterogenous landscape needs to be represented, heightening the needs for data and for accurate integration with other sub-models that simulate ecological or biophysical dynamics. The requirement for agents to have a particular geographical location raises further modeling questions on the drivers of relocation, the type and extent of spatial externalities imposed on other agents, the types of linkages between agents and locations (e.g. one to one or one to many), and the ways in which the heterogeneity of spatial attributes and agents' preference may interact. Once these complex design and representation issues are addressed, ABMs may help to explore dynamic paths of coupled SES and, thus, to design proper policies to resolve key societal issues. This exploration is especially relevant when dynamics involve abrupt changes, crises and critical transitions stemming from cumulative effects of social interactions and adaptive behavior, since other modeling tools based on perfect information and fixed static rational behavior may be misleading.

This paper reviews progress in spatial agent-based models along the lines of four methodological challenges introduced

and discussed below, in particular building on the 12 papers that constitute this Thematic Issue. We critically reflect on how these papers contribute to the progress toward meeting the methodological challenges in the ABM field and reflect on the future work that is required. The paper also serves as a preface for the Thematic Issue on 'Spatial agent-based models for socio-ecological systems'.

1.1. Progress in agent-based models for socio-ecological systems up to date

Several key publications from the turn of the last century highlighted pioneering work on spatial ABM for SES (Grimm, 1999; Kohler, 2000; Gimblett, 2001). Early work in ABMs of land-use and land-cover change was summarized by Parker et al. (2002, 2003). Since then, substantial work has been done to move the field forward. Several excellent reviews on spatial and environmental ABMs have done a comprehensive analysis of the published work and crystallized the knowledge per subject area. Bousquet and Le Page (2004) review the shifts in paradigms when studying ecological complexity toward more explicit integration of the role of human actions, and a consequent rise of ABM application for ecosystem management. Matthews et al. (2007) synthesize the knowledge on the use of ABM in land-use science, focusing on spatially explicit and heterogenous representation of the environment. Torrens (2010) summarizes the applications of ABMs in physical and human geography focusing on opportunities ABMs offer for extending spatial sciences with multi-disciplinary perspectives. In the light of complexity theory and mutual feedbacks between human actions and environmental consequences, An (2012) reviews various decision models used in ABMs for SES, highlighting their strengths and weaknesses. In addition to compiling the knowledge on modeling coupled SES with ABMs, scholars have produced reviews on the application of the method to each of the subsystems: socio-economic (Tesfatsion and Judd, 2006; Safarzynska and van den Bergh, 2010; Chakraborti et al., 2011; Marks, 2012) and ecological systems (Grimm et al., 2005). Substantial attention has also been given to systemizing approaches to empirically characterize and parameterize agents' behavior in ABMs for SES (Janssen and Ostrom, 2006; Robinson et al., 2007; Windrum et al., 2007; Valbuena et al., 2008; Smajgl et al., 2011).

The journal Environmental Modelling and Software (EMS) in particular is an active platform for publicizing research involving ABMs for SES. The topics of environmental applications of ABMs are diverse: energy and climate change mitigation (Zhang et al., 2011; Gerst et al., 2013), farming (Bithell and Brasington, 2009; Schreinemachers and Berger, 2011), urban development (Brown et al., 2004; Haase et al., 2010; Filatova et al., 2011), water management (Feuillette et al., 2003; Smajgl et al., 2009; Yu et al., 2009; Moglia et al., 2010; van Oel et al., 2010; Murillo et al., 2011), ecosystem management (Batten, 2007; Moreno et al., 2007; Anselme et al., 2010; Brede and De Vries, 2010; Simon and Etienne, 2010), and tourism (Anwar et al., 2007). Individual-based modeling involving coupled SES (de Almeida et al., 2010; Perez and Dragicevic, 2010) as well as methodological issues related to ABMs (Polhill et al., 2006) also receive attention.

This Thematic Issue aims to continue this effort to assemble knowledge and experience of applying ABMs to explore the dynamics of coupled SES, and to critically assess the progress with respect to key challenges identified in the field in relation to the papers presented here.

1.2. Challenges for current and future work

As discussed above, the architecture of ABMs is attractive to explore the dynamics of complex coupled SES. Yet, throughout the

years several challenges and research priorities have been identified. Drawing from discussions at key international meetings on spatial ABMs for SES (including AAG, iEMSs, GLP, etc.) as well as from the previous reviews in the field, we identify four categorical challenges addressed in the thematic issue papers:

- **Modeling agents' behavior**: how are agents' decision models designed and parameterized to capture behavior and interactions in the real world situations? Some ABMs are highly stylized, grounding agent behavior in one of the predominant theories of an application domain. Others reject any theoretical preconsiderations and focus on replicating behavior that is observed empirically. Creating a balanced specification and parameterization of agent behavior in ABMs in relation to (i) one of the competing decision-making theories in social sciences and to (ii) empirical observations is a major challenge. Moreover, it is important to differentiate between and assess the implications of behavioral assumptions. Based on social science theories, approaches that address the explicit modeling of cognition, power, emotions, and the dynamics of beliefs and other insights from psychology can be followed. Here, the reliance on entirely statistically-parameterized versus adaptive behavioral rules largely affect models' outcomes. Moreover, behavioral assumptions may range between perfectly informed rational agents to bounded rational ones. The modeler must make conscious choices regarding an explicit modeling of behavioral change (e.g. learning, switching to different strategies, changes in agent's preferences and perceptions), and an accepted protocol to guide these choices has not been developed (Meyfroidt, 2012).
- **Sensitivity analysis, verification and validation**: how reliable and robust are the outcomes of an ABM? The nature of ABMs ideally calls for micro-scale information on agents behaviors and interactions between agents. This level of detail implies a high number of model parameters to which model performance is potentially sensitive. Models may also be constructed using alternative decision models or representations of spatial structure. Finally, models often contain stochastic elements. The sensitivity of the model to these features has to be systematically tested. Like models in any field, ABMs needs to be assessed with respect to the soundness of their construction and their success in replicating real-world trends and patterns (verification and validation). Sensitivity analysis, verification, and validation become especially vital when ABMs are applied in a policy context to inform management challenges.
- **Coupling socio-demographic, ecological, and biophysical models**: when being applied to study complex SES dynamics, ABMs focusing primarily on human behavior need to be integrated with other types of models. How is this integration implemented in terms of feedback mechanisms and software coupling? Integration of various modeling components is strenuous for any type of modeling (Voinov and Shugart, 2013), including ABMs. Often models are loosely coupled with one-way feedback between social and environmental systems. Accuracy and validity of a model with respect to the way these feedbacks are implemented and the way they affect resilience of SES is rarely tested (Schlüter et al., 2012). It can also be challenging to identify linking variables and gather real-world data needed to link models.
- **Spatial representation**: The spatial representation and modeled landscapes in ABMs often need to capture spatial heterogeneity of inputs and outputs across multiple spatial scales. While the first two challenges are applicable for all ABMs, this one is inherited by spatial ABMs from the necessity to have a landscape. How should the spatial scale of analysis be

defined in ABMs, and how can multiple scales of analysis be combined in the same model? How can discrete representations of space be combined with network or diffusion models?

This thematic issue contains a series of innovative papers that address one or more of these challenges. Such overview provides an up-to-date evaluation of the way in which ABMs have been able to address the challenges and live up to the expectations as well as identifying the remaining challenges.

2. Representation of the thematic challenges

2.1. Modeling agents' behavior: design and parameterizing of agent decision models

Several of the papers in the special issue explicitly address the design and parameterization of agents' behavior, using alternative methods. Smajgl and Bohensky (2013) advances the practice of parameterizing agents' decisions by using an iterative approach. It combines household survey data, expert validation and census data to parameterize household responses to changes in fuel price, distinguish different response types and scale these from the survey data to the larger population. This approach bases both the identification of agent types as well as their behavioral responses on empirical information gathered by conducting an extensive survey.

In the IAMO-LUC ABM, which aims to study land use change affected by payments for ecosystem services, Sun and Muüller (2013) introduce an innovative hybrid approach combing Bayesian belief networks (BBNs) and opinion dynamics models (ODM) in a spatial context. BBNs endow agents with the ability to make land-use decisions under uncertainty while explicitly keeping links between factors shaping these decisions. Agents equipped with BBNs 'brains' make decisions using both qualitative empirical information, e.g. beliefs and attitudes of stakeholders derived from participatory workshops, and quantitative data collected via household surveys. The combination of BBNs and ODM allows the model to go beyond perfect economic rationality in agents' behavior and accounting for social influences.

When studying tourist demand in response to various climate change adaptation strategies of the Alpine touristic sector in Italy, Balbi et al. (2013) model eight tourist profiles. The authors build upon previous efforts of empirical ABMs to identify classes of agents from own field survey data (snapshot of the current situation) and put this practice forward by complementing it with other data sources such as an empirical literature review and historical data on the frequency and duration of stays from 1985 to 2008. The three alternative adaptation strategies of winter tourism industry were the result of local stakeholders discussion supported with empirical cost parameters per type of investment. Thus, the behavior of tourists and corresponding parameters in the AWS1.0 ABM were identified based on past, current and possible future agents' choices.

Touza et al. (2013), use the management of deer in Scotland in their spatial agent-based model to examine co-operative behaviors amongst individuals managing an ecological resource. The model simulates two landscape scenarios: one comprised only of shooting estates and one where the land is given over entirely to biodiversity conservation. In both scenarios, agents own and manage a single cell that contains a population of deer. While the agents in each landscape scenario will have differing opinions about the deer population on their cell (i.e. a valuable revenue resource for shooting estate owners, and a pest by biodiversity conservationists), they do share a common objective in the management of the deer population, which is to attain maximum payoffs through effective management of this ecological resource. Touza et al. analyze how these payoffs and ecology dynamics influence the co-operative behavior of the agents in each landscape scenario.

A simple modeling approach was adopted by Caillault et al. (2013) to assess the influence of three different incentive networks on the land use decisions taken by farmers. Three network scales were used: "global" which related to policy driven land use practices, "social" which defined shared/collective land-use practices and "local" which were land-use practices influenced by neighbors' actions. At each time step, the farmer receives incentives from each network encouraging him to implement a new land use practice; however the land-use options viable for his land are constrained by the "age" of the current land-use type, and the new land-use practices are prioritized by the farmers against the viability of their land to support its implementation. Although the model is relatively simplistic, the authors are able to show how a combination of network incentives can affect fragmented landscapes.

On a related topic, Polhill et al. (2013) study how different policy instruments provide incentives for the protection of species on farm land. Similarly to the paper by Caillault et al. (2013), no extensive work is done on empirically quantifying the decision rules. Rather, based on knowledge of the study area, a case-based reasoning algorithm is implemented, which reacts to the difference between the mean profit received and the aspirations of the farmers. By accounting for fluctuations in market prices, the reaction of farmers to different incentives as well as different intensities of these incentives can be calculated.

In their model of the growth of residential housing and energy consumption in Vienna, Gaube and Remesch (2013) use census data to define and parameterize distributions of seven household types, which represent different demographic cohorts with alternative preferences for residential dwellings and energy consumption behavior. Household status evolves during the model run according to a demographic cohort model that includes household division and agglomeration. Representative household populations are drawn from joint distributions of census data. Residential mobility (triggers for relocation) events are parameterized based on results from previous statistical models. Empirically defined weighting factors for environmental amenities, centrality, transport access, social prestige, cost effectiveness, and living space are used to rank alternative residential properties by relocating households. Thus, these authors demonstrate new methods to empirically simulate the evolution of household structures and use this evolution to trigger changes in agent decision making.

Other EMS papers demonstrate techniques that can be instrumental in understanding the agents' behavior (Brown et al., 2004; Anwar et al., 2007; Batten, 2007; Smajgl et al., 2009; Brede and De Vries, 2010; de Almeida et al., 2010; Haase et al., 2010; Moglia et al., 2010; Perez and Dragicevic, 2010; Simon and Etienne, 2010; van Oel et al., 2010; Filatova et al., 2011; Murillo et al., 2011; Schreinemachers and Berger, 2011; Zhang et al., 2011).

2.2. Sensitivity analysis, verification and validation of ABMs

In an ABM examining the effects of land set-asides on skylark populations in Denmark, Parry et al. (2013) use Bayesian Analysis of Computer Code Outputs (BACCO) to perform sensitivity analysis that identifies the model parameters to which model output is most sensitive. This method allows for global sensitivity analysis (examining the effects of multiple parameter variations) with a higher level of computational efficiency than previous methods, solving an important challenge related to the computational complexity of sensitivity analysis of ABMs. The method essentially fits a stochastic meta-model between input parameters and output

data, providing the opportunity for both qualitative visualization and quantitative analysis of parameter sensitivity. Such meta-models can provide comprehensive information about the relationship between model parameters and outputs previously only provided through formal analysis of closed-form equilibrium models. The authors use this method to identify input parameters that are empirically uncertain and to which the model is most highly sensitive.

Balbi et al. (2013) performed a sensitivity analysis for the most relevant tourists' behavioral parameters for each of the eight touristic profiles under different scenarios of climate change. Each behavioral parameter was first varied separately considering the maximum realistic variation, and then tested under all possible combinations of high and low values of the four parameters, to which the model output is most sensitive. The AWS1.0 model was capable of reproducing two main observed patterns (the seasonal peaks of the tourism demand and the relative expenses per tourist profiles). In addition, the model was validated through a social experiment where local stakeholders tried to anticipate the outcomes of the model after they were briefed about the assumptions. The stakeholders' expectations confirmed the aggregated ranking of adaptation strategies that emerged in the model.

Marohn et al. (2013) validated their model based on the extent to which the model could reproduce observed land use for different population clusters. Similar comparisons were made for other key parameters. This validation indicates to what extent the model initialization can reproduce the current system state, but does not necessarily indicate the model validity for simulating change.

Sun and Müüller (2013) performed a careful validation of their ABM. First, the performance of land-user agents' behavior based on BBNs was tested. The authors used 80% of their survey sample (509 households and 1973 plots) to conduct network learning, and used the remaining 20% of the cases for model verification. Their model has high predictive power, with about 85% predicted accurately. Sun and Müller tested the robustness of these results by repeating the random selection of 80%–20% from the pool of the respondents four times, as well as by varying the share of training and test datasets (70%–30% and 50%–50%). Agents' behavior driven by BBNs was subject to sensitivity analyses at both the household and plot levels. In addition to this quantitative "validation" the model was qualitatively peer reviewed by experts who judged upon relevance and reliability of the BBN results.

Similarly, additional papers in EMS put a special accent on sensitivity analysis (Polhill et al., 2006; Anwar et al., 2007; Bithell and Brasington, 2009; Murillo et al., 2011; Gerst et al., 2013) and validation (Feuillette et al., 2003; de Almeida et al., 2010; Haase et al., 2010; Perez and Dragicevic, 2010; Simon and Etienne, 2010; Schreinemachers and Berger, 2011).

2.3. Coupling socio-demographic, ecological, and biophysical models to informing management challenges

Robinson et al. (2013) loosely coupled a new agent-based model with the ecosystem process model BIOME-BGC to investigate how different land management strategies impact on the carbon storage capacity of land in an exurban residential setting. Loose coupling provides the new land change modeling framework with flexibility to enable the authors to link in other ecosystem models at a later stage; however the authors acknowledge there are pros and cons associated with the loose coupling approach. However, the approach allows the authors to link land-market and land-management decisions directly to carbon storage.

While Balbi et al. (2013) model adaptation of Alpine touristic sector to climate change, there is no direct coupling of economic and biophysical models. Instead authors used data on the scenarios of climate change from 2011 to 2050 from other models: projected weather conditions, concerning temperature and snow cover, were produced with the SkiSim 2.0 model considering the downscaled climate signals of the regional climate model REMO UBA M 20064 under the A1B and B1 SRES scenarios of IPCC. Future economic scenarios, e.g. type of market competition and composition and total number of tourists, also served as an input to the AWS1.0 ABM. The aggregated socio-economic output indicators could be coupled with relevant environmental consequences.

Both Parry et al. (2013) and Rebaudo and Dangles (2013) couple land-management models with models of mobile animal/insect populations. Parry et al.'s model examines the effects of removal of set-asides on skylark populations, holding socio-economic factors, such as agricultural management activities, fixed. Farm management and set-asides affect a vegetation growth model, which affects available habitat for skylarks. Individual skylarks are represented as spatially mobile agents, who gain subsistence from available habitat and whose populations evolve through a life cycle model. This paper provides an excellent example of coupling of models that operate over different spatial scales, and of the coupling of fixed and mobile agent models. Rebaudo and Dangles' model also holds agricultural management choices fixed, but examines the decisions of farmers to invest in integrated pest management control strategies, based on their knowledge and the pest status of neighboring fields. The population-scale pest model operates through a logistic growth and dispersal function. The paper provides an alternative example of how processes at different scales can be integrated. Thus, these two papers represent different approaches to coupling agricultural land management models with species population models, as one species model operates as an individual-based model and the other operates at a population scale.

Marohn et al. (2013) have coupled an agent-based model of land-use decisions to a biophysical model of plant growth, water and soil dynamics. Central in the interaction between the socio-economic model and the biophysical model is plant growth, as this affected by both land management and the biophysical conditions, thus providing an interface between the socio-economic and biophysical sub-systems.

Finally, Polhill et al. (2013) couple an agent-based model of farmer decision responses to agri-environmental policy incentives to a meta-population model in order to explore which incentives at what intensity have the best cost/benefit relation in terms of the protection of species richness. Interestingly the authors identify for some incentives a threshold in the increase of benefits for biodiversity upon a further intensification of the policy incentives. Non-linearities in the effects of policy incentives on biodiversity are dependent on context and the ways in which the policies are implemented. This way the coupled model system provides an analysis of the consequences of policy incentives, not only for decision making, but also for the biodiversity preservation at which the policies are targeted. This approach is unique in identifying potential non-linear responses to policies in the fully coupled system.

EMS has further examples of other coupled socio-ecological models that are important for management applications (Moreno et al., 2007; Bithell and Brasington, 2009; Anselme et al., 2010; Simon and Etienne, 2010; Schreinemachers and Berger, 2011).

2.4. Spatial representation

Spatial representation of diversity in the environmental context of the agents as well as the divergent outcomes of the model simulations is an important component of many models. Different approaches are used to represent spatial heterogeneity in model inputs and outputs in the papers in this issue. The papers do

effectively represent the suite of current methods for spatial representation in ABMs. However, the papers do not systematically indicate the rationale of the choices toward choosing a specific spatial resolution or extent. In many cases the spatial representation is chosen based on the typical data available and consistent with the spatial variation in the processes described.

Smajgl and Bohensky (2013) use census data to scale their agent types to a large geographic extent. Consequently, the spatial resolution of the model is bounded by the administrative units for which census information was available. Gaube and Remesch (2013) intersect "city area types" with administrative districts to create 59 spatial divisions for the city of Vienna, thereby also modeling at a fairly coarse spatial resolution. Rebaudo and Dangles (2013) model at the farm scale, using spatial neighbor relationships to also define social neighbor influences. Parry et al. (2013) also run their model at a farm scale, but their individual-based skylark model contains territory location and foraging models that create more complex spatial network patterns. Marohn et al. (2013) use a high spatial resolution in the model as in their model an assessment of the spatially variable biophysical impacts of land change decisions is important. These include a.o. soil dynamics, which can only be simulated in a very heterogenous landscape if a high spatial resolution is considered. Sun and Muüller (2013) used GIS data on heterogenous characteristics of land (lot size, soil quality, distances, slope) enriched by participatory mapping data (indications of land use, landmarks and boundaries) from 17 villages in China. The results of the IAMO-LUC ABM simulation can potentially serve as an input to other environmental models (e.g., habitat fragmentation models or water run-off models).

Barnaud et al. (2013) have not only looked at the ways in which spatial diversity can be represented in models, but have also analyzed the role of spatial presentations of modeling results on the use of models as a negotiation tool with stakeholders. Interestingly, they found that while spatial representations provide stakeholders with a comprehensive frame for negotiations, they also caused stakeholders to focus more on division of space, rather than a focus on multifunctional use of spatial resources.

Dynamic social space (a network through which opinion dynamics is transmitted) and heterogenous bio-physical space (the landscape) coexist in the IAMO-LUC framework (Sun and Muüller, 2013). Land-use decisions are influenced by peer agents connected through a small-world network. Since the data was collected at the village and household level, the social network for opinion dynamics is implemented in a hierarchical way linking farmers within one village with a stronger probability than linking them to farmer of another community.

Spatial heterogeneity and analysis also plays an important role in many other EMS papers (Anwar et al., 2007; Moreno et al., 2007; Bithell and Brasington, 2009; Yu et al., 2009; Anselme et al., 2010; Haase et al., 2010; Perez and Dragicevic, 2010; Simon and Etienne, 2010; van Oel et al., 2010).

3. Discussion and conclusions

The above discussion indicates that the challenges for ABMs of SES are explicitly addressed by the papers in this thematic issue. However, to what extent does this mean that the challenges for agent-based modeling as they were identified in earlier review papers are addressed? In this section we critically reflect on the progress the papers from this thematic issue have achieved along the line of four key challenges.

Substantial progress has been made in recent years to empirically support the choice of agent behavioral models and parameterize the decision rules based on empirical data. Many agent-based models of land change and other environmental applications now employ a range of empirical techniques to create a typology of different decision making types and parameterize the decision making rules in the model based on household survey results (Robinson et al., 2007; Valbuena et al., 2008; Smajgl et al., 2011). The papers by Smajgl and Bohensky (2013), Balbi et al., 2013 and Sun and Muüller (2013) are good examples of this empirical approach. Gaube and Remesch (2013) extensively use census data and results of other statistical models to define agents and their residential mobility rules. Although the behavioral models in the other papers are also loosely based on observations of decision making in the real world, they do not make use of intensive empirical analysis of empirical data to derive the decision rules employed. From the papers, it is clear that a mix of methodologies is used and that the selection of the behavioral model applied is not always informed by a deep analysis.

In a recent review of decision making in land change, Meyfroidt (2012) concludes that in land-change science, the representation of the cognitive aspects of decision making is deficient. His overview of alternative decision making models is synthesized by the notion that (i) land-use choices result from multiple decision-making processes and rely on various motives, influenced by social norms, emotions, beliefs, and values toward the environment; (ii) social–ecological feedbacks are mediated by the environmental cognition, that is, the perception, interpretation, evaluation of environmental change, and decision-making; and (iii) human agents actively re-evaluate their beliefs, values, and functioning to adapt to unexpected environmental changes. The latter is especially vital for ABM, as the methodology is based on the assumption of adaptive behavior. While the field is generally quite advanced in applying various learning techniques (Brenner, 2006), there are still only few applications of artificial learning and evolutionary dynamics in the domain of spatial and socio-ecological ABMs (Kellermann and Balmann, 2006; McNamara and Werner, 2008; Ettema, 2011; Magliocca et al., 2011), with little guidance on which of them is most empirically sound. In order to design the agent behavior in ABMs of SESs, much more work is needed to better understand alternative decision-making processes and their interactions, the underlying environmental cognition and the role of context in determining which representation of agent behavior is suited in a specific case. Advancing these understandings requires a combination of empirical investigation, theory development and model-based testing of alternative behavioral specifications. Comparing modeling results to observed dynamics by means of validation will help to discover which assumptions about behavior and its adaptive change are most realistic.

In order to have validation of models achieve the objective of enhancing our understanding of the ways in which the model representation deviates from reality, the validation efforts need to move beyond a simple comparison of model outputs with observations (Messina et al., 2008). The papers in this issue illustrate that the need for such analysis is acknowledged in the ABM community. Three of the included papers (Balbi et al., 2013; Parry et al., 2013; Sun and Muüller, 2013) have stepped beyond a simple validation by doing a full sensitivity analysis of their model to find which model mechanisms are providing robust results and where model assumptions are critical determinants of the results. As the specification of the behavioral assumptions will always contain a high degree of uncertainty, such sensitivity analysis can show if this uncertainty critically influences the results of the model. While the methods for sensitivity analysis and validation have advanced, there are still challenges to trace back poor validation results and high sensitivities to the underlying mechanisms implemented in the model. Only when the uncertainties and errors can be attributed to the specific components in the design or parameterization of specific decision rules it is possible to learn where our

representation of reality in the model is incorrect; as such allowing us to learn about SES functioning and identifying critical knowledge gaps in representing these systems. Such iterative process in which validation results are used to further inform SES representation is not addressed explicitly in the papers in this thematic issue. Often validation results are presented and no further action is taken based on these.

Due to their flexibility in the choice of temporal and spatial scales and scheduling of dynamics at various resolutions, ABMs offer wide opportunities for coupling socio-demographic, ecological, and biophysical models. Yet, one needs to decide how this integration will be implemented in terms of feedback mechanisms and software coupling (Verburg, 2006; Voinov and Shugart, 2013). This requires identification of a set of variables at various spatial scales to represent hypothesized chains of causality and feedbacks scheduled at certain time scales. Parker et al. (2008) distinguish between 3 ways to link SES: (i) one-way linkage when natural science models are inputs to social systems, (ii) a chain of one-way linkages natural–social–natural with natural system input and output models potentially differing, and (iii) two-way linkage with endogenous determination of common variables in natural and social system models through interactions between social and environmental systems (for example, timber harvest decisions depend on carbon storage, and climate change due to timber harvest subsequently affects carbon storage rates, and thus harvest incentives). The majority of ABMs in coupled SES in general, and in this thematic issue in particular, represent the cumulative dynamics of human behavior, with some individual-based models (IBM) simulating ecological dynamics (Parry et al., 2013; Rebaudo and Dangles, 2013). While scholars involved in modeling SES highlight the importance of two-way linkages, current research still tackles type (i) or (ii) linkages primarily. Balbi et al. (2103) is a one-way linkage model with climate change and economic growth scenarios coming as inputs to the ABM, which offers a potential for associating aggregated of socio-economic output indicators with relevant environmental consequences, thus heading to type (ii) models. A chain of one-way linkages, i.e. type (ii), is the primarily way of coupling socio-demographic ABMs, ecological process or IBM, and biophysical models, as demonstrated by Parry et al. (2013), Rebaudo and Dangles (2013), Robinson et al. (2013) and Polhill et al. (2013). The paper by Marohn et al. (2013) is the only one in the current issue realizing two-way linkage, i.e. type (iii): plant growth is determined endogenously, being affected by both land management and the biophysical conditions. Implementation of such two-way linkages in coupled SES models is an essential direction of research. It is especially vital for studying non-linear interactions between human and natural systems, when gradual changes in one subsystem may lead to abrupt critical transitions in the other one (Matthews et al., 2007; Filatova and Polhill, 2012). While empirical evidence of such regime shifts, crisis and catastrophic behavior is growing (Scheffer, 2009), development of models (including ABMs) that are able to simulate two-way feedback between human and environment system and predict crossing critical thresholds are still under way.

In part through improved methods for parameterizing agent populations and decision models, ABMs have improved the detail of their spatial representation of heterogenous human influences, as seen in the models of Gaube and Remesch (2013), Marohn et al. (2013), and Sun and Muüller (2013). From an ecological perspective, field data is also used to create detailed spatial representations of the behavior of species (Parry et al., 2013) and species biodiversity (Polhill et al., 2013). Progress is being made also on more complex challenges, such as the need to create compound spatial unit definitions that combine different land covers under a single management unit (Robinson et al., 2013), to generating simulated landscapes whose properties match an empirical distribution, to develop algorithms to divide large parcels into new subdivisions (Wickramasuriya et al., 2013), and to generate new dwellings in intensifying landscapes (Gaube and Remesch, 2013). On the output side, new methods from outside the ABM world could be used visualizing simulated landscapes, especially using novel three-dimensional visualization techniques (Walz et al., 2008; van Lammeren et al., 2010; Griffon et al., 2011).

As the ABM field advances, significant progress is observed in designing and parameterizing agent decision models, in approaches to verify and to validate ABMs as well as in ways to handle sensitivity analysis, in coupling ABMs with other models and in the richness of spatial representation. Yet, the new societal challenges and, consequently, the demands for modeling that is capable of supporting policies to manage coupled SES are growing. While this special issue provides a nice display of various applications of ABM in environmental and land sciences, further methodological developments are required. Advances in collecting micro-level and interaction data (field work and role-playing games, laboratory experiments, social networking apps and online services) may help in specifying theoretically-solid and empirically-justified adaptive decision rules and evolution of agents' attributes, and provide data for validation at multiple scales. Progress in integrated modeling may offer new ways of software coupling, while newly available georeferenced environmental and socio-economic data at various resolutions opens new opportunities to fully exploit potential of the ABM methodology.

Acknowledgments

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