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Current Opinion in Environmental Sustainability

Opportunities to improve impact, integration, and evaluation of land change models

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Land change modeling supports analyses, assessments, and decisions concerning land management by providing a platform for both encoding mechanisms of land-change processes and making projections of future land-cover and land-use patterns. Approaches have ranged from pattern-based methods, such as machine learning models, to structural or process-based methods, such as economic or agent-based models. Selection of the appropriate modeling approach for a given scientific or decision making purpose is essential. Additionally, we argue that more needs to be done to develop and disseminate methods for evaluating land-change models (LCMs). The profession needs better data to support the use of LCMs, integration of models that operate at various scales, and combinations of models that address both positive and normative aspects of land use and land cover patterns and dynamics

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Current Opinion in Environmental Sustainability 2013, **5**:452–457

This review comes from a themed issue on **Human settlements and industrial systems**

Edited by **Peter H Verburg**, **Ole Mertz**, **Karl-Heinz Erb** and **Giovana Espindola**

For a complete overview see the Issue and the Editorial

Available online 12th September 2013

http://dx.doi.org/10.1016/j.cosust.2013.07.012

Introduction

Models of patterns, change, and dynamics in land use and land cover have been important tools for land-change science [1] and land-system science [2] and application. Land-change models (LCMs) can serve a variety of purposes and come in different forms. Early reviews of LCMs tended to originate in landscape ecology and focus either on biophysical land cover [3] or on human land-use change [4–6]. A challenge identified in these earlier reviews was how to represent processes of human decision making in these models as a mechanism by which land changes are made. Work over the last decade has focused on representing human decision making, coupling between human and environmental systems, and addressing questions about environmental sustainability challenges through model coupling [7]. Thus, more recent reviews have provided more complete coverage of models that integrate across human and natural systems and explicitly represent how human actors behave in these systems [2,8,9], which are advances that improve the suitability of LCMs for addressing environmental sustainability challenges. The National Research Council in the US commissioned a study [10••] to review the current state of modeling to support understanding and projecting land-change systems. As a result of this review, we argue that the land-change science community can improve its use of models by: firstly, better aligning modeling approaches with the goals of their application, secondly, better integrating LCMs with available data and models, and finally, improving and disseminating model evaluation procedures.

At a fundamental level, modeling is a process that provides a platform for formally encoding inferred or deduced relationships. While many conceptual models can be purely descriptive in nature, we focus in this review on models expressed in a form that permit simulation and projection; these forms generally have some mathematical or algorithmic expression. Models used for land change vary from those that are strongly oriented towards describing *patterns*, regardless of whether or not the reason for the patterns or dynamics are based on land-change theory, to those that express dynamics as *processes* that mimic those that are understood to generate changes in patterns based on observations in the field and theory [8]. Models in the natural sciences are most often quantitative. However, computer algorithms permit qualitative expressions in the form of conditional statements (i.e. if…then…), which allow for context sensitive descriptions of human actions that may be necessary to express knowledge generated by the social sciences through a mixture of quantitative and qualitative methods [11].

Once formally expressed, models provide tools that can support a variety of science and application purposes that might be arranged according to their emphasis on *projection* versus *explanation*. While most applications in which models are deployed require some of both, the relative emphasis on these two goals can be a key distinguishing characteristic that affects the appropriate choice of approach. Projection aims to produce an estimate of the quantity and/or spatial allocation of land use or cover at some point in the future, under some specified set of conditions. Assumptions concerning stationarity (i.e. constant conditions or processes) vary in their comprehensiveness, with trend projection (i.e. business-as-usual) models maintaining a very strong assumption of stationarity. Explanation purposes might be aimed at identifying which land-use decision theory better explains observed land-change outcomes, or whether variable interactions produce non-linear dynamics or threshold effects. The projection and explanation goals are pursued simultaneously when models are used to evaluate scenarios that involve interventions in the system that are aimed at achieving some outcome. For example, models used for policy evaluation generally need to represent the mechanisms by which changes are happening while also making projections about the effects of the policy.

Modeling approaches

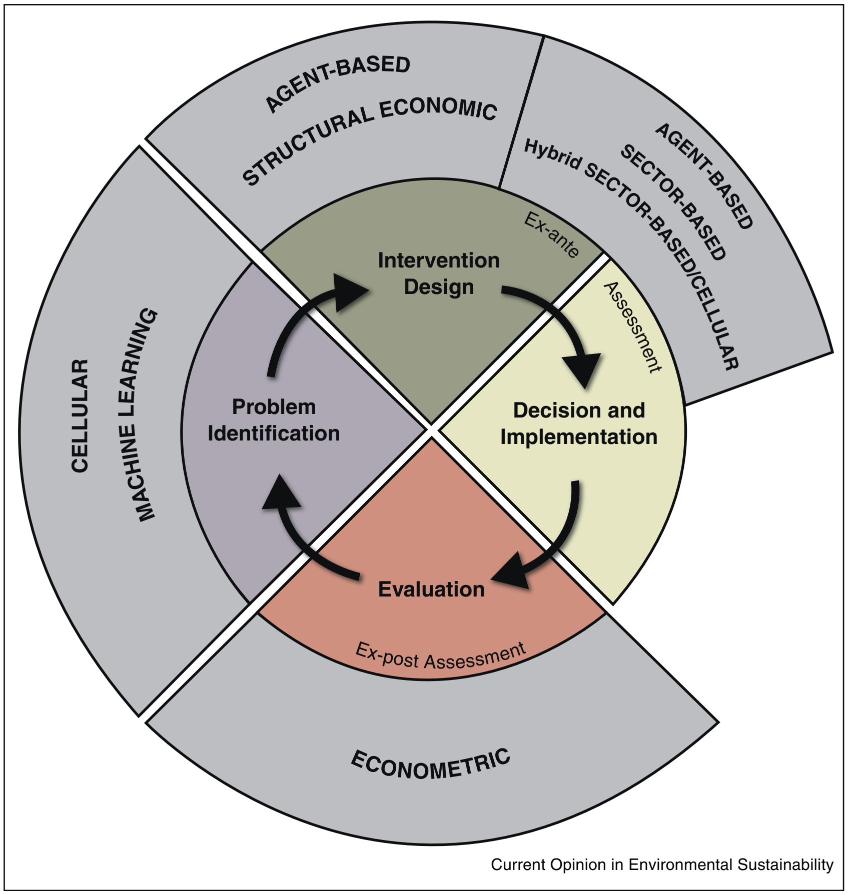
We identify five key types of modeling approaches based on their relative emphasis concerning pattern versus process and concerning projection versus explanation. *Machine learning* approaches, including some statistical models, focus largely on projection of patterns, and rely on algorithms that encode relationships between land-use changes and the characteristics of locations where they are most likely to occur, represented with spatial variables such as soil quality and distance to roads and cities. Variable selection is driven by theory and methods include artificial neural networks [12], classification and regression trees (CART) [13], and logistic regression [14]. *Cellular* approaches simulate changes over time by combining maps of likelihood with spatial interaction effects and, sometimes, information about broader scale drivers of land demand [15•]. While these models represent processes of change based on locations, they often do so based on relationships of observed patterns and are limited in their ability to represent decision making processes. Two different types of economic models are used to describe land change as a market process and are distinguished primarily by the scale at which they operate. *Sector-based economic models* focus on inputs and outputs, and trade among regions and sectors, to identify demand for land of different types. These models are usually structural, in that they explicitly represent supply and demand as contributing to market equilibria [16•]. *Spatially disaggregated economic models* are designed according to micro-economic theory to help investigators to understand changes in land-use and cover as an outcome of individual decisions [17,18]. These can be structural or in reduced form, in which the specific mechanisms may be only implicitly represented through specification of the model and variables selected. Econometric approaches are often used to estimate the effects of variables used in spatially disaggregated models [19]. Finally, *agent-based* approaches are structural, in that their content and form are designed by the modeler to represent the processes and interactions that are believed to be operating to produce observed land changes [20,21]. While many agent-based models are built on economic theory, their flexibility allows incorporation of nearly any theory of decision making and land change (e.g. based on social, cultural, historical, or cognitive theories) [9,22] that can be written in algorithmic form.

Aligning modeling approaches with model goals

We argue that models need to be carefully aligned with purposes to which they are put because the modeling approaches have different structures, accommodate different levels of process detail, and have different data requirements. For example, machine-learning approaches tend to be useful for extrapolations under assumptions of business-as-usual (e.g. stationarity) because they are based on trends from past observations, whereas structural approaches are more useful for exploring causal processes and possible effects of external shocks or policy interventions because they are based on specifications of actors and their decision processes. Therefore, the scientific and application context dictates the usefulness of any given modeling approach.

Any given application will express the policy planning and evaluation process in a unique way, with feedbacks and iterations among different steps; however an idealized schematic [23] serves to distinguish four key roles for models in environmental sustainability applications: problem identification, intervention design, *ex-ante* assessment, and *ex-post* assessment, i.e. evaluation (Figure 1). At the early stages of problem identification, when understanding the nature of patterns and trends is needed and understanding of process details may be weak, machine learning and cellular approaches are particularly useful [24,25]. As thinking moves towards designing interventions (e.g. regulatory, fiscal, or market-based remedies), structural economic or agent-based approaches that describe the nature of interactions among actors in the system become more useful. These two types of models are, for example, helpful in transportation planning [26], and can be used to explore possible non-linear interactions and unintended consequences of policies [27•,28]. *Ex-ante* assessments that compare competing interventions also require more structural approaches to test possible implications of the interventions. For example, assessments of biofuel regulations and subsidies have relied heavily on sector-based economic models [16•]. Most *ex-post* evaluations take the form of spatially disaggregated econometric analyses that compare outcomes with and without the policy intervention, for

Figure 1



Land change modeling approaches (outer circle) placed within the context of the policy and decision making cycle (inner circle) [10••].

example by using before/after comparisons [29] or selecting geographically similar control groups where the policy was not implemented [30•].

Better integration with available data and models

Improved observational data

We argue that better integration of observational data in three areas can improve LCMs. First, finer spatial and temporal resolution data that can be integrated with socio-economic and biogeophysical data are needed to promote coupling of LCM's with other model types (e.g. models of transportation or urban hydrology). Modelers need to learn the value of more detailed data relative to the conceptual constructs underlying the models, and need to alter the models to accommodate finer scale representations where necessary. There is also value in capturing and distributing data that describe additional dimensions of land use such as function, cultural importance, density, tenure, management, and value, because lack of data causes these dimensions to be ignored in LCMs. Second, it is critical to maintain the temporal and spatial continuity of data concerning land and related characteristics derived from satellite-based observations, airborne-based observations and survey-based observations. The constellation of newer and smaller satellite and airborne platforms is one route to fill gaps in traditional satellite coverage. New image processing algorithms that use objects rather than pixels as the unit of analysis may provide new types of data to link satellite-based land use and land cover information with land management information [31] to harmonize global and regional data with heterogeneous local data sources such as cadastral and land value data. Third, better data on land-change actors and their beliefs, preferences, and behaviors are critical to improving the predictive ability of LCMs and the usefulness of these models in evaluating the consequences of alternative policies [22]. Ideally, these data will be spatially explicit and available for multiple time points so that they can specify dynamic spatial land-change processes. There are several promising ad hoc approaches to collecting data on land-change actors, such as using point-of-sales data on individual purchases, location-aware technologies that track individuals in space and time, and internet-based data retrievals that reveal social networks [32]. The proprietary and privacy issues involved in accessing these data are not trivial, and efforts to resolve these issues are ongoing.

Integration across scales

A model's design is frequently based on the dominant processes and data at the specific scale of application, thus particular LCMs tend to apply to specific processes and scales. Therefore, the scale of the application is an important criterion in model selection. At the same time, land change is influenced by cross-scale processes, such as tele-couplings through trade, the climate and hydrological systems [33] as well as feedbacks across spatial and temporal scales within socio-ecological systems [34]. In current LCMs, such cross-scale interactions are captured in various ways. In its simplest form, process representations that apply to one scale are applied, within the model, to another scale. Decision making concerning allocation of land resources in sector-based models is based on individual economic rational choice modeling, but applied to representative agents using average values valid for large world regions, thus making the assessments vulnerable to scaling errors [35]. Alternatively, multiple models are linked in a hierarchical manner to represent the processes influencing land change at various scales. A typical example of this approach is the *top-down hierarchical model* chain, in which global models constrain land areas allocated by more detailed cellular models [36,37]. This approach assumes a dominance of the coarse-scale representations over the more detailed local models. In contrast, a bottom-up approach that builds on detailed models [38,39] gives more weight to local land-use decisions, but has not yet been implemented in operational models. We argue that advancing the representation of cross-scale dynamics in LCMs is essential to our ability to represent processes such as tele-coupling, indirect land use change and adaptation to climate change at multiple scales. It is necessary to increase our understanding of feedback mechanisms across scales in order to implement such processes in operational models.

Integrating positive and normative approaches to modeling

While the land change modeling work described here is aimed at explanation and/or prediction based on evidence-based accounts of land systems (i.e. positive approaches), substantial opportunities exist in the use of approaches that incorporate human values and goals in the modeling of land systems for design and planning (i.e. normative approaches). Optimization approaches like genetic algorithms and simulated annealing can be used to evaluate tradeoffs in ecosystem services resulting from alternative landscape patterns [40], to compare the relative performance of protected areas in providing suitable habitat [41], to consider alternative possible landscape patterns [42], and to complement both design-based approaches [43] and process models. It becomes possible to explore both the outcomes that are most beneficial and the processes that might produce those outcomes by integrating and comparing positive and normative modeling approaches to a given problem [44]. We view this integration as an important and promising future direction for the development of LCMs.

Evaluating land change models

The ways in which models are employed and evaluated requires considering the purposes to which models are put, just as model choice must be aligned with the goals of the particular application. We argue that four topics require development and adoption in the practice of model application: sensitivity analysis, pattern validation, uncertainty sources, and structural validation. *Sensitivity analysis* examines the variation in model output in response to variation in a set of model elements. Sensitivity analysis should be constructed to consider variations in the model output due to differences in the input data, model parameters, initial conditions, boundary conditions, and model structure [45]. The most common approach to evaluate model performance is *pattern validation*, in which model outputs parameterized for some historical case, often in the form of maps, are compared with observations for that case [46]. A major challenge is to select an assessment metric that is mathematically rigorous, intuitively interpretable, and practically useful. It is important to explore the range of outcomes possible from a model [47] and model dynamics [48] in sensitivity analyses and pattern validation, because of problems with equifinality [49], which describes the situation where a given pattern could have been generated by more than one model, and multifinality [50], where a given model can generate more than one pattern. *Uncertainty sources* include parameters, structure, processes and process interactions. Uncertainty in forecasting future states can derive from non-stationarity in processes, input variables or boundary conditions. Explicit recognition of stationarity assumptions and exploration of data for evidence of non-stationarity are important steps in acknowledging and understanding model uncertainty. *Pattern validation* describes the match between model outputs and observed outputs, while *structural validation* focuses on the match between the processes in the model and the processes operating in the real world. A combination of qualitative and quantitative measures is necessary for structural validation. Empirical estimation (e.g. with econometric methods) of model parameters, quantitative examination of the maintained assumptions in the model [51], and quantifying spatial variability across multiple runs of a model [47] have all been offered as quantitative approaches to structural validation, but more work is needed.

Conclusions

A variety of approaches have been taken to model changes in land use and land cover, ranging from approaches oriented towards extrapolating past patterns to approaches aimed at representing the environmental and human-decision processes driving these changes. Alignment of model choices with modeling goals is critical to successful application of these models, especially as they relate to projection of patterns and explanation of processes. Integration of LCMs with improved observational data, across scales, and across positive and normative modeling approaches offers promise for advancing relevance of models to environmental sustainability challenges. Finally, work is need to improve and disseminate use of model evaluation approaches.

Acknowledgments

We thank the additional members of the study committee, Lawrence Band, Kass Green, Elena Irwin, Atul Jain, Eric Lambin, Karen Seto, Billie L. Turner II, and all attendees at our workshop in Chapel Hill, NC, Feb 2012. We gratefully acknowledge the funding support for this study from the U.S. Geological Survey and National Aeronautics and Space Administration.

References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. Turner BL II, Lambin EF, Reenberg A: **The emergence of land change science for global environmental change and sustainability**. *Proc Natl Acad Sci USA* 2007, **104**:20666-20671.

2. Rounsevell MDA, Pedroli B, Erb KH, Gramberger M, GravsholtBusck A, Haberl H, Kristensen S, Kuemmerle T, Lavorel S, Lindner M *et al.*: **Challenges for land system science**. *Land Use Policy* 2012, **29**:899-910.

3. Baker WL: **A review of models of landscape change**. *Landsc Ecol* 1989, **2**:111-133.

4. Briassoulis H: **Analysis of land use change: theoretical and modeling approaches**. In *The Web Book of Regional Science*. Edited by Loveridge S. West Virginia University; 2000 http://www.rri.wvu.edu/regscbooks.htm.

5. Agrawal C, Green GM, Grove JM, Evans TP, Schweik CM: *A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice. Gen. Tech. Rep. NE-297*. U.S. Department of Agriculture, Forest Service, Northeastern Research Station; 2002.

6. Verburg PH, Schot P, Dijst M, Veldkamp A: **Land use change modelling: current practice and research priorities**. *GeoJournal* 2004, **61**:309-324.

7. Clark WC: **Sustainability science: a room of its own**. *Proc Natl Acad Sci USA* 2007, **104**:1737-1738.

8. Overmars KP, Verburg PH, Veldkamp T: **Comparison of a deductive and an inductive approach to specify land suitability in a spatially explicit land use model**. *Land Use Policy* 2007, **24**:584-599.

9. An L: **Modeling human decisions in coupled human and natural systems: review of agent-based models**. *Ecol Model* 2012, **229**:25-36.

10. •• NRC, *Advancing Land Change Modeling: Needs and Research Requirements*. Washington, DC: National Academy Press; 2013.
The report provides an expert assessment of the current state of land change modeling and provides several detailed recommendations for future development of these tools for application within land change science and management.

11. Cheong S, Brown DG, Lopez-Carr D, Kok K: **Mixed methods in land-change research: towards integration**. *Trans Inst Br Geogr* 2011, **37**:8-12.

12. Pijanowski BC, Brown DG, Shellito BA, Manik GA: **Using neural nets and GIS to forecast land use changes: a land transformation model**. *Comput Environ Urban Syst* 2002, **26**:553-575.

13. Etter A, McAlpine C, Wilson K, Phinn S, Possingham H: **Regional patterns of agricultural land use and deforestation in Colombia**. *Agric Ecosyst Environ* 2006, **114**:369-386.

14. Li S, Verburg PH, Shihai L, Wu J, Xiaobing L: **Spatial analysis of the driving factors of grassland degradation under conditions of climate change and intensive use in Inner-Mongolia, China**. *Reg Environ Change* 2012, **12**:461-474.

15. • van Vliet J, Hurkens J, White R, van Delden H: **An activity-based cellular automaton model to simulate land-use dynamics**. *Environ Plan B* 2012, **39**:198-212.
The authors extend the cellular automata approach to modeling by linking land uses to population densities and human activities. The approach improves the process representation capabilities of the cellular approach.

16. • Golub AA, Hertel TW: **Modeling land-use change impacts of biofuels in the GTAP-BIO framework**. *Clim Change Econ* 2012, **3**:1250015.
The authors demonstrate the value of the sectoral modeling approach in identifying the impacts of changes in product demand on trade and their subsequent effects distal land-use change.

17. Irwin EG, Bockstael NE: **Land use externalities, open space preservation, and urban sprawl**. *Reg Sci Urban Econ* 2004, **34**.

18. Filatova T, van der Veen A, Parker DC: **Land market interactions between heterogeneous agents in a heterogeneous landscape — tracing the macro-scale effects of individual trade-offs between environmental amenities and disamenities**. *Can J Agric Econ* 2009, **57**:431-459.

19. Nelson G, De Pinto A, Harris V, Stone S: **Land use and road improvements: a spatial perspective**. *Int Reg Sci Rev* 2004, **27**:297-325.

20. Parker DC, Manson SM, Janssen MA, Hoffmann MJ, Deadman P: **Multi-agent systems for the simulation of land-use and land-cover change: a review**. *Ann Assoc Am Geogr* 2003, **93**:314-337.

21. Matthews R, Gilbert N, Roach A, Polhill J, Gotts N: **Agent-based land-use models: a review of applications**. *Landsc Ecol* 2007, **22**:1447-1459.

22. Meyfroidt P: **Environmental cognitions, land change, and social-ecological feedbacks: an overview**. *J Land Use Sci* 2013, **8**:341-367.

23. Vedung E: *Public Policy and Program Evaluation*. edn 4. Transactions Publishers; 1997.

24. Araujo MB, Nogues-Bravo D, Reginster I, Rounsevell M, Whittaker RJ: **Exposure of European biodiversity to changes in human-induced pressures**. *Environ Sci Policy* 2008, **11**:38-45.

25. Verburg PH, Schulp CJE, Witte N, Veldkamp A: **Downscaling of land use change scenarios to assess the dynamics of European landscapes**. *Agric Ecosyst Environ* 2006, **114**:39-56.

26. Borning A, Waddell P, Forster R: **UrbanSim: using simulation to inform public deliberation and decision-making**. In *Digital Government: E-Government Research, Case Studies, and Implementation.* Edited by Chen H, Brandt L, Gregg V, Traunmueller R, Dawes S. Springer-Verlag; 2008:439-463.

27. • Bell AR, Riolo RL, Doremus J, Brown DG, Lyon TP, Vandermeer J, Agrawal A: **Fragmenting forests: the double edge of effective forest monitoring**. *Environ Sci Policy* 2012, **16**:20-30.
The authors illustrate how agent-based modeling can be used to identify possible unintended consequences of policy choices, by representing the interactions between the various actors in a system.

28. Agrawal A, Brown DG, Rao G, Riolo RL, Robinson DT, Bommarito M: **Interaction between organizations and networks in common-pool resource governance**. *Environ Sci Policy* 2013, **25**:138-146.

29. Lubowski RN, Plantinga AJ, Stavins RN: **What drives land-use change in the United States? A national analysis of landowner decisions**. *Land Econ* 2008, **84**:529-550.

30. Andam KS, Ferraro PJ, Pfaff A, Sanchez-Azofeifa GA, Robalino JA:
• **Measuring the effectiveness of protected area networks in reducing deforestation**. *Proc Natl Acad Sci USA* 2008, **105**:16089-16094.

The authors present a rigorous econometrically based matching approach to test the effectiveness of protected areas. The matching approach exploits similarities in locations that that have undergone and not undergone a policy intervention to test its effects.

31. Zhu Z, Woodcock CE: **Object-based cloud and cloud shadow detection in Landsat imagery**. *Remote Sens Environ* 2012, **118**:83-94.

32. Goodchild MF: **Citizens as voluntary sensors: spatial data infrastructure in the world of Web 2.0**. *Int J Spatial Data Infrastruct Res* 2007, **2**:24-32.

33. Lambin EF, Meyfroidt P: **Global land use change, economic globalization, and the looming land scarcity**. *Proc Natl Acad Sci USA* 2011, **108**:3465-3472.

34. Verburg PH: **Simulating feedback in land use and land cover change models**. *Landsc Ecol* 2006, **21**:1171-1183.

35. Easterling WE: **Why regional studies are needed in the development of full-scale integrated assessment modelling of global change processes**. *Global Environ Chang* 1997, **7**:337-356.

36. Verburg PH, Eickhout B, van Meijl H: **A multi-scale, multi-model approach for analyzing the future dynamics of European land use**. *Ann Reg Sci* 2008, **42**:57-77.

37. Lawrence PJ, Feddema JJ, Bonan GB, Meehl GA, O'Neill BC, Oleson KW, Levis S, Lawrence DM, Kluzek E, Lindsay K *et al.*: **Simulating the biogeochemical and biogeophysical impacts of transient land cover change and wood harvest in the Community Climate System Model (CCSM4) from 1850 to 2100**. *J Climate* 2012, **25**:3071-3095.

38. Rounsevell MDA, Robinson DT, Murray-Rust D: **From actors to agents in socio-ecological systems models**. *Philos Trans R Soc B* 2012, **367**:259-269.

39. Smajgl A, Brown DG, Valbuena D, Huigen MGA: **Empirical characterisation of agent behaviours in socioecological systems**. *Environ Model Softw* 2011, **26**:837-844.

40. Nelson E, Polasky S, Lewis DJ, Plantinga AJ, Lonsdorf E, White D, Bael D, Lawler JJ: **Efficiency of incentives to jointly increase carbon sequestration and species conservation on a landscape**. *Proc Natl Acad Sci USA* 2008, **105**:9471-9476.

41. Ceballos G, Ehrlich PR, Soberon J, Salazar I, Fay JP: **Global mammal conservation: what must we manage?** *Science* 2005, **309**:603-607.

42. Duh J-D, Brown DG: **Generating prescribed patterns in landscape models**. In *GIS, Spatial Analysis, and Modeling.* Edited by Maguire D, Goodchild M, Batty M. ESRI Press; 2005: 423-444.

43. Nassauer JI, Opdam P: **Design in science: extending the landscape ecology paradigm**. *Landsc Ecol* 2008, **23**:633-644.

44. Guzy MR, Smith CL, Bolte JP, Hulse DW, Gregory SV: **Policy research using agent-based modeling to assess future impacts of urban expansion into farmlands and forests**. *Ecol Soc* 2008, **13**:37. [online] *http://www.ecologyandsociety.org/vol13/iss1/art37/*.

45. Alcamo J, Schaldach R, Koch J, Kölking C, Lapola D, Priess J: **Evaluation of an integrated land use change model including a scenario analysis of land use change for continental Africa**. *Environ Model Softw* 2011, **26**:1017-1027.

46. Pontius RG Jr, Boersma W, Castella J-C, Clarke K, de Nijs T, Dietzel C, Duan Z, Fotsing E, Goldstein N, Kok K *et al.*: **Comparing input, output, and validation maps for several models of land change**. *Ann Reg Sci* 2008, **42**:11-47.

47. Brown DG, Page SE, Riolo R, Zellner M, Rand W: **Path dependence and the validation of agent-based spatial models of land use**. *Int J Geogr Inform Sci* 2005, **19**:153-174.

48. Ligmann-Zielinska A, Sun L: **Applying time-dependent variance-based global sensitivity analysis to represent the dynamics of an agent-based model of land use change**. *Int J Geogr Inform Sci* 2010, **24**:1829-1850.

49. Beven K, Freer J: **Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology**. *J Hydrol* 2001, **249**:11-29.

50. Brown DG, Aspinall R, Bennett DA: **Landscape models and explanation in landscape ecology — a space for generative landscape science?** *Prof Geogr* 2006, **58**:369-382.

51. Kuminoff N: **Decomposing the structural identification of non-market values**. *J Environ Econ Manage* 2009, **57**:123-129.