Advancing Land Change Modeling: Opportunities and Research Requirements

ISBN
978-0-309-28833-0

146 pages
6 x 9
PAPERBACK (2013)

Committee on Needs and Research Requirements for Land Change Modeling; Geographical Sciences Committee; Board on Earth Sciences and Resources; Division on Earth and Life Studies; National Research Council

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Geographical Sciences Committee

Board on Earth Sciences and Resources

Division on Earth and Life Studies

NATIONAL RESEARCH COUNCIL
OF THE NATIONAL ACADEMIES

THE NATIONAL ACADEMIES PRESS
Washington, D.C.
www.nap.edu

Prepublication Copy—Subject to Further Editorial Revision

THE NATIONAL ACADEMIES PRESS 500 Fifth Street, NW Washington, DC 20001

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This study was supported by Grant No. G10AP00104 between the National Academy of Sciences and the United States Geological Survey (USGS) and Grant No. NNX10AT12G between the National Academy of Sciences and the National Aeronautics and Space Administration (NASA). Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the organizations or agencies that provided support for the project.

International Standard Book Number 0-309-0XXXX-X
Library of Congress Catalog Card Number 97-XXXXX

Additional copies of this report are available for sale from the National Academies Press, 500 Fifth Street, NW, Keck 360, Washington, DC 20001; (800) 624-6242 or (202) 334-3313; http://www.nap.edu/.

Cover:

Printed in the United States of America

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ACKNOWLEDGMENTS

This report has been reviewed in draft form by individuals chosen for their diverse perspectives and technical expertise, in accordance with procedures approved by the National Research Council's Report Review Committee. The purpose of this independent review is to provide candid and critical comments that will assist the institution in making its published report as sound as possible and to ensure that the report meets institutional standards for objectivity, evidence, and responsiveness to the study charge. The review comments and draft manuscript remain confidential to protect the integrity of the deliberative process. We thank the following individuals for their participation in the review of this report:

Richard Aspinall, University of Aberdeen, Aberdeen
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Although the reviewers listed above provided many constructive comments and suggestions, they were not asked to endorse—nor did they see—the final draft of the report before its release. The review of this report was overseen by Kate Beard-Tisdale, University of Maine, Orono. Appointed by the Division on Earth and Life Studies, she was responsible for making certain that an independent examination of the report was carried out in accordance with institutional procedures and that all review comments were carefully considered. Responsibility for the final content of this report rests entirely with the authoring committee and the National Research Council.

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SUMMARY

People are constantly changing the land surface through construction, agriculture, energy production, and other activities. Changes both in how land is used by people (land use) and in the vegetation, rock, buildings, and other physical material that cover the Earth's surface (land cover) can be described and future land change can be projected using land-change models (LCMs). LCMs are a key means for understanding how humans are reshaping the Earth's surface in the past and present, for forecasting future landscape conditions, and for developing policies to manage our use of resources and the environment at scales ranging from an individual parcel of land in a city to vast expanses of forests around the world.

The U.S. Landsat satellites have provided an invaluable 40-year record of global land cover change, providing input to LCMs, yielding new scientific insights, and informing policy on issues ranging from agriculture to regional planning and disaster relief. A recent explosion in the number and types of new land observations and monitoring data, model approaches, and computational infrastructure has ushered in a new generation of LCMs that are capable of new applications associated with human-environment systems in increasing detail. A wide variety of modeling approaches has been developed, each with different strengths, weaknesses, and applications. However, with increasing recognition of the role of human action in affecting change in the Earth system, greater demand for evaluations and forecasts of these impacts, and a greater variety of data sources available, it is timely to evaluate these approaches and their relative value for particular types of applications.

At the request of the U.S. Geological Survey and the National Aeronautics and Space Administration, the National Research Council established a committee to describe various LCM approaches, suggest guidance for their appropriate application, and describe ways to improve the integration of observation strategies into the models (see Box S.1 for the complete committee charge). To carry out its charge, the committee gathered input from stakeholders in the LCM community at committee meetings, a workshop, and through an online questionnaire. Based on this input, a review of the literature, and their own experience, the committee examined the primary modeling approaches and their most suitable applications and identified several key ways to improve LCMs for decision makers and scientists. This report provides a summary and evaluation of several modeling approaches, and their theoretical and empirical underpinnings, relative to complex land-change dynamics and processes, and identifies several opportunities for further advancing the science, data, and cyberinfrastructure involved in the LCM enterprise. Because of the numerous models available, the committee focused on describing the categories of approaches used along with selected examples, rather than providing a review of specific

BOX S.1
Statement of Task

A National Research Council committee will review the present status of spatially explicit land-change modeling approaches and describe future data and research needs so that model outputs can better assist the science, policy, and decision-support communities. Future needs for higher resolution and more accurate projections will require improved coupling of land-change models to climate, ecology, biogeochemistry, biogeophysical, and socioeconomic models; improved data inputs; improved validation of land-change models; and improved estimates of uncertainty associated with model outputs. The study will provide guidance on the verification strategies and data, and research requirements needed to enhance the next generation of models. In particular, the study committee will:

1. Assess the analytical capabilities and science and/or policy applications of existing and emerging modeling approaches.
2. Describe the theoretical and empirical basis and the major technical, research, and data development challenges associated with each modeling approach.
3. Describe opportunities for improved integration of observation strategies (including ground-based survey, satellite, and remote sensing data) with land-change modeling to improve land-change model outputs to better fulfill scientific and decision making requirements.

models. Additionally, because all modeling approaches have relative strengths and weaknesses, the report compares these relative to different purposes.

LAND CHANGE MODELING APPROACHES

A wide variety of LCMs has been developed to examine land change processes and to make land use and land cover projections. The committee grouped these individual models into six categories of modeling approaches:

1. Machine-Learning and Statistical approach uses observations of past land-cover or land-use changes to calibrate parametric or non-parametric relationships between those changes and spatially and temporally specific predictors,
2. Cellular approach integrates maps of suitability for land cover or land use with neighborhood effects and information about the amounts of change expected to project future changes,
3. Sector-Based Economic approach uses partial and general equilibrium structural models to represent supply and demand for land by economic sectors within regions based on overall economic activity and trade,
4. Spatially Disaggregate Economic approach estimates structural or reduced form econometric models to identify the causal relationships influencing the spatial equilibrium in land systems, and
5. Agent-Based approach simulates the decisions and actions of heterogeneous land-change actors that interact with each other and the land surface to make changes in the land system.

6. Hybrid approaches encompass applications that combine different approaches into a single model or modeling framework.

The first five approaches are arranged roughly in order from least to most focused on process. The approaches that rely on data about land-change patterns, including Machine Learning and Statistical, and Cellular, tend to use land-cover information from satellite imagery, and relationships based on observed changes in the past. These approaches are useful for projecting observed land-cover changes over short periods into the future, but often have limited ability to evaluate conditions not observed in the past. The more process-based approaches, such as Sector-Based Economic, Spatially Disaggregate Economic, and Agent-Based, make greater use of social science information about land-change processes. These latter approaches provide more realistic representations of the processes of change that can be used to evaluate a wider range of alternative futures, but they are more challenging to calibrate and validate and may provide only qualitative information about possible future land-change outcomes.

The best modeling approach to use depends on the application. The relative advantages of the approaches for particular purposes can be used in various policy and decision-making contexts and the modeling approaches tend to serve different roles within the context of the four-stage policy cycle: (1) problem identification, (2) intervention design, (3) decision and implementation, or (4) evaluation. Machine Learning and Statistical and Cellular Modeling approaches are most suitable for problem identification because, though they lack the richer structural detail about process needed to evaluate the effects of changes in policy structure, they are easy to implement and can provide valuable descriptions and projections of patterns and trends. Agent-Based and Structural Economic approaches are useful for intervention design because they provide a means for exploring interactions in the land system and for assessing the possible effects of policies or decisions *ex ante*. Once policies or decisions have been implemented, the *ex post* effects of these implementations can be evaluated using reduced-form econometric models that compare observable outcomes either before and after the intervention or in an intervention area and a comparable location. Understanding the underlying structures, assumptions, and data requirements of different modeling approaches is critical for understanding their applicability for various scientific and decision-making purposes.

IMPROVING LAND CHANGE MODELS

New observations, improvements in modeling capability and computer infrastructure, and advances in understanding the theoretical and social context of land change have created opportunities to improve LCMs to support research and decision making on current and future land change. Opportunities are grouped into five categories: (1) advances in LCMs themselves, (2) advances in land observation strategies, (3) advances in cyberinfrastructure, (4) advances in other infrastructure, and (5) developing and using best practices in model evaluation. Within each opportunity category are two to four specific initiatives selected by the committee that represent important near-term (three to six years) approaches to realizing the potential for LCMs to better serve an integrated Earth system science enterprise, our understanding of sustainability in human interactions with the environment, and decision making about land-related management and policy.

Opportunities for Advances in LCMs

Advancement of process-based models

While data- (or pattern-) based models have succeeded in using land-cover data products and contributing to land-change science and applications, process-based models of land change are not as mature. Better process-based models are necessary for understanding interactions and feedbacks between people's actions and land change and for simulating policy scenarios to evaluate the impacts of a potential policy change on land use. Further developing these approaches to make the best use of available data will advance the goal of evaluating past efforts and possible future implementations of new policies and management strategies to address sustainability challenges.

Cross-scale integration of LCMs

Because land-change processes occur at multiple scales, LCMs need to link patterns and processes across multiple scales. These kinds of links require that models account for connections between distant locations of consumption and production of land-based commodities, and their network interactions, and employ new analytical methods that link models of global, regional, and local processes of land-based decision making. Better understanding of how to include representations of heterogeneous actors linked through social networks is also needed to better represent both the top-down and bottom-up causes of land change.

Integration with other Earth system models

Better dynamic coupling of LCMs with a variety of Earth system models would improve the ability to understand and project the direct and indirect effects of land management decisions and policies on the tradeoffs among various ecosystem services (e.g., food and fiber production, maintenance of biodiversity, and carbon storage). Land cover change model results have typically been used as input to other environmental models. However, coupling LCMs and environmental models would enable feedbacks between environmental and land-change dynamics to be represented and investigated, which is important for long-term forecasting.

Bridging LCM with optimization and design-based approaches

Most LCMs seek to explain and predict changes in land use and land cover using either a process- (structural) or pattern-based approach. In contrast, decisions about policy require the ability to determine, given a choice among a set of possible policies or designs, which policies will generate landscape patterns that are both plausible and acceptable for society. An important challenge is to further integrate LCMs with optimization, which is extremely computationally intensive, and design-based approaches, which require the engagement of human designers and landscape architects, in order to integrate considerations of what could be with what should be.

Opportunities in Land Observation Strategies

The second set of opportunities makes use of the flood of new data to inform the development of the next generation of land change models.

Improved capture and processing of remotely sensed data

A variety of developments in Earth observations have the potential to spur advances in land change modeling. Data collected at finer resolutions, coupled with object-based image analysis tools, offer the opportunity to develop models that better represent diverse features in the built and natural environments. Data available at finer temporal resolutions and over longer time periods, including the free Landsat archive and historical aerial photo records, present the opportunity to better understand the dynamics and non-stationarity of land-change processes and incorporate that understanding into LCMs. Data on the three-dimensional structure of the landscape from LiDAR and other active sensors permit the development of models that can represent quantitative differences in attributes of land cover (like biomass) and land use (building density). Creative uses of satellite measurements like the nighttime lights products to estimate human settlement densities, energy use, and economic activity provide opportunities to develop spatially, temporally, and thematically richer inputs to LCMs. Hyperspectral sensors, like those on an array of smaller satellites, permit more detailed information about canopy composition that might be useful in parameterizing models that represent land-management (e.g., fertilization and irrigation) behaviors. Maximizing the ability to capture, interpret, and manage these kinds of data and incorporate them into new LCMs represents a significant opportunity for advancing the ability to use observational data to inform new modeled processes and projections.

Integration of heterogeneous data sources

Some land change decisions require information not typically included in LCMs—including land function, land-use density, land tenure, land management, and land value—or information at a variety of spatial and temporal resolutions. Integrating these data with socioeconomic and biogeophysical data would facilitate coupling of LCMs and other types of models such as those of climate change, ecosystem services and biodiversity, energy use, and urbanization.

Data on land-change actors

Land change is the cumulative result of the decisions and interactions of a variety of actors—households, firms, landowners, policymakers at local, regional and global levels. Microdata on actors are collected by the Bureau of the Census, the Department of Agriculture, and other agencies. Better integration of data on these actors and their beliefs, preferences, and behaviors with Earth Observation data is critical for improving the ability of LCMs to project future land change and to evaluate the consequences of alternative policies.

Making systematic land-use observations

Many observations of natural and human systems must be measured from ground-based systems, which are commonly divided among multiple agencies and geographies. Possible programs like a national land observatory or national survey of land resources could be developed to collect spatially referenced data with linked records on land patches, land parcels, and land users. Such a program would improve the ability of the LCM community to learn more about land change processes, test hypotheses, and improve predictive ability.

Opportunities in Cyberinfrastructure

A number of the opportunities noted above have the potential to find solutions through contemporary advances in cyberinfrastructure.

Crowd sourcing and distributed data mining

The ability to collect and analyze large amounts of data on individual behaviors, much of which is referenced in time and space, has grown tremendously over the past decade. Crowd sourcing and distributed data mining are two primary examples of this kind of development. Combining these data collection approaches with LCMs has the potential to extend the reach of LCM results to a variety of users and could also lead to better construction, calibration, and validation of structural or process-based models. However, privacy and proprietary concerns will have to be resolved.

High-performance computing

Cyberinfrastructure is increasingly able to meet the computational demands of some of the modeling approaches outlined above. Advances in computing power are increasingly based on deployment of multiple processing cores and increasing numbers of processors. Taking advantage of this enhanced computing power requires that models be written to take advantage of parallel processing, i.e., partitioning computational tasks among multiple processors running simultaneously. Greater volumes of distributed data storage provide opportunities to incorporate data over larger areas and at finer resolutions into the next generation of models.

Opportunities for Infrastructure to Support Land Change Modeling

Progress in land-change modeling is partially impeded by the continued reinvention of modeling environments, frameworks, and platforms by various research groups. Opportunities to improve the research infrastructure and help to overcome this barrier are summarized below.

Model and software infrastructure

Developing a consistent infrastructure for documenting and sharing models and software would help avoid duplication of effort among various constituents in the LCM community. The challenge for the community is to assemble the existing infrastructure and enhance it to serve two purposes: (1) advancement of the fundamental understanding and representation of land-change processes and (2) integration of a wide range of biophysical and socioeconomic models for evaluating the impacts of land change.

Data infrastructure

A data infrastructure would provide access to a common set of data resources that are necessary for running and validating models of land change. Infrastructure developments that aim to support compilation, curation, and comparison of the heterogeneous data sources for input to land change models would advance this kind of access directly.

Community modeling and governance

A consistent and widely adopted community modeling and governance infrastructure is important to support developments in LCM. Such an infrastructure would provide mechanisms for making decisions and advancing modeling capabilities within a broad community and toward specific, achievable goals and capabilities. In particular, it would provide a framework for reaching community agreement on specific goals and endpoints to move modeling and data capabilities forward.

Model Evaluation

There are a variety of practices that can enhance land-change modeling to make it more scientifically rigorous and useful in application. Some of these practices are established but not always followed, while others require more research to test and establish.

Sensitivity analysis is an established procedure whereby the investigator examines the variation in model output due to specific amounts of variation in model input, parameter values, or structure.

Pattern validation requires matching the choice of a metric that compares model output to data with the purpose of the modeling exercise for the particular application; how this is best done requires additional research.

Structural validation, or validating model processes, remains a challenging task in part because the underlying processes that give rise to observed land-use patterns are themselves not fully observable. Continued research on how to validate the maintained assumptions that are necessary in order to even specify a model would benefit model validation and projections.

CONCLUSION

Multiple communities of science and practice in critical areas associated with environmental sustainability, including food, water, energy, climate, health, and urbanization, are adopting land-change models (LCMs) to help with understanding and improving human-environment interactions at multiple scales. While LCMs have already contributed in all of these areas, an opportunity exists to consolidate the understanding of land system interactions, refine and improve the best available modeling approaches, and make significant progress towards new analytical and predictive capabilities. The time is ripe to envision, plan for, and invest in the next generation of land-change models for an increasingly interdisciplinary scientific enterprise that takes advantage of the best available knowledge, data and computing resources.

If appropriately planned and executed, the next generation of models can be increasingly process based, link processes in social and natural systems from the parcel scale to regional and global scales and make use of better methods for process validation, in order to enhance both their predictive skill and their utility for policy analyses. New LCMs can also be routinely used, appropriately and with greater confidence, for a wider range of scientific and policy purposes, supporting better understanding of land systems, the effects of economic and social processes on their dynamics, and their effects on important environmental and social outcomes. Taking advantage of a wider range of Earth observation data types to enhance their spatial and temporal detail and the categories of information they represent, future LCMs can integrate these with data on the human attitudes, preferences, and behaviors related to land change, both from traditional and a growing number of novel sources for social data. Highly interconnected data systems, well-documented model and software code, and a well functioning community of land-change modelers can support the scientific enterprise to advance these goals.

Near-term intellectual and resource investments (three to six years) in the science of and infrastructure to support advancements in LCMs could help achieve these goals. This report outlines a number of specific areas that are ripe for advancement. Such investments have the potential to move forward our understanding of, ability to predict, and tools for analyzing policy related to key environmental sustainability challenges.

1

The State of Land Change Modeling

Land change, which includes changes in land use, land cover, and environmental functions related to human-driven processes, can be described and projected through land change models (LCMs). Models of land change are applied from the level of individual parcels within urban areas to vast expanses of global forests and are used to explain, forecast, and project past, present, and future land and landscape conditions important for decision and policy making at many different scales. Due in part to an explosion in observational and monitoring data on land cover and spatially explicit environmental and socioeconomic data, as well as advances in analytical and technological infrastructure, LCM is now entering a phase with new possibilities for development that could help address a large range of decisions that affect human-environment systems. These advances permit problems to be addressed in greater detail and with better representation of the underlying processes. Researchers continue to push LCMs to treat increasingly complex problems and to support robust measures for addressing them.

These developments are taking place in the context of emerging national and international attention to global climate change and sustainability, be it America's Climate Choices (NRC, 2011a,b), the U.S. Global Change Research Program (2012), or the new sustainability initiative, Future Earth, of the International Council of Science (Reid et al., 2010). These and other programs seek a more integrative understanding of human-environment systems and cooperation between the science and decision-making communities to tackle critical problems associated with human-environment systems. Having their basis in models that emphasize changes in land use or land cover, LCMs are confronted with new demands as a result of these integrated research and problem-solving goals.

In this context, the time is appropriate to examine LCMs and to determine their applicability for a myriad of scientific and decision-making applications; their fit with current themes, concepts, and data; and the improvements needed to provide the quality of output increasingly expected of them. To this end, the authoring committee was asked by the U.S.

Geological Survey and the National Aeronautics and Space Administration to review the present status of spatially explicit LCM approaches and describe future data and research needs so that model outputs can better assist the science, policy, and decision-support communities. They were also asked to provide guidance on the verification strategies and data and research requirements needed to enhance the next generation of models. The committee was asked specifically to (1) assess the analytical capabilities and science and/or policy applications of existing and emerging modeling approaches; (2) describe the theoretical and empirical basis and the major technical, research, and data development challenges associated with each modeling approach; and (3) describe opportunities for improved integration of observation strategies (including ground-based survey, satellite, and remote sensing data) with LCM to improve LCM outputs to better fulfill scientific and decision-making requirements.

In addressing these tasks, the committee necessarily had to place bounds on the scope of this assessment. Rather than reviewing specific models, the committee focused on the need to understand differences among modeling approaches which are implemented in various ways and for different purposes. While this means that many specific models, of which there are likely thousands of instances, are not specifically mentioned in the report, the categories of modeling approaches addressed are used in the vast majority of these models. Additionally, because of the emphasis of the sponsoring agencies on Earth observations, we place greater emphasis on modeling approaches for which these observations are relevant inputs, though not to the exclusion of considering other important data requirements.

Despite existence of a broad literature on modeling coupled with land-transportation systems, we chose to focus on modeling approaches that can use transportation patterns as inputs to land change processes. Approaches to modeling transportation systems themselves were outside the scope of our assessment. Additionally, while significant efforts have been made to develop spatial optimization approaches to be used for developing land use and cover patterns that optimize some specific objectives (what are referred to as *normative* models), these have not been well integrated with models focused on understanding and forecasting land changes (what we refer to later as *positive* models), the third chapter of the report identifies opportunities for doing so. The report primarily focuses its assessment on *positive* models.

THE SIGNFICANCE OF LAND SYSTEMS AND LAND CHANGE MODELS

Land systems, from cityscapes to landscapes, have long been examined to understand the causes and consequences of their spatial organization (e.g., Beckman, 1972), and various models have been developed to guide in the explicit design of these systems to deliver desirable societal and environmental outcomes (e.g., Waddell et al., 2003). These traditions notwithstanding, attention to changes in land systems and to their modeling has been elevated in importance over the past quarter century as awareness of the role of land systems in environmental change and sustainability has increased (Reid et al., 2010; Rounsevell et al., 2012; Watson et al., 2000). Changes in land systems have significant consequences for local to global climate and environmental change (Foley et al., 2005; Pielke, 2005). For this reason, decisions and policies related to land systems de facto will serve as strategies for mitigating and adapting to these changes and to reaching a more sustainable world (NRC, 2010a,b). Various scientific and practitioner communities seek to address new types of questions and problems with LCMs, such as configuring land systems to ameliorate climate change and developing scalable models of land change with improved capacity to be coupled with other environmental and socioeconomic models addressing specific topics. These efforts have been facilitated by major improvements in the amount and quality of data, methods, and technologies relevant for observing and monitoring, analyzing, and modeling land system change (NRC, 2003, 2008). The resulting mosaic of LCMs is large, tackles various parts of land system change differently, and includes models with different strengths for various science or practitioner communities.

In general, scientists build LCMs to test theories and concepts of land change associated with human and environment dynamics and to explore the implications of these dynamics for future land changes under scenarios that elude real-world observation. The policy and practitioner communities are concerned with guiding land use decision making, for which LCMs provide value by enabling exploration of the possible outcomes of those decisions. These distinctions notwithstanding, LCMs inform and are used by many research and practitioner communities to address topics related to the processes of and outcomes from land change across a wide range of domains of relevance to environmental change and sustainability, including:

1. Land-climate interactions;
2. Water quantity and quality;
3. Biotic diversity, ecosystem function, and trade-offs among ecosystem services;
4. Food and fiber production;
5. Energy and carbon (sequestration); and
6. Urbanization, infrastructure, and the built environment.

LCMs are especially relevant for these and related topics because land systems are expressed spatially as land uses and land covers; these and related attributes result from dynamics in land systems and from a series of human-environment interactions (Turner et al., 2007). LCMs are used to describe, project, and explain the changes in and dynamics of land use and cover, but they can also represent the dynamics in these broader land system interactions. They consider social and biophysical conditions, processes, and variables to address the land system at large, or to target specific social (e.g., vulnerability to hazards) or biophysical (e.g., water quality) outcomes.

Dynamics of land use and land cover are complex, involving multiple social and biophysical processes and outcomes. To account for this complexity, LCMs may be linked or coupled with climatic, ecological, biogeochemical, biogeophysical, and socioeconomic models

(Polasky et al., 2008; Robinson et al., 2007), such that other models are an input to the LCM, the LCM is an input to other models, or the models are coupled bidirectionally.

Complexity is present in land system dynamics because of social and biophysical heterogeneity, spatial and social interactions, natural and human adaptation, and feedbacks among system components. This leads to variation in outcomes by geographical location, social group, or ecosystem type, and to nonlinear dynamics that can complicate attempts to validate and predict models. Virtually all LCMs produce outcomes that are spatially explicit, either in terms of land use and cover or specific biophysical (e.g., NPP, leaf area index, roughness) or socioeconomic (e.g., income levels and distributions, age) variables. Complexity typically enlarges the sensitivity of model outcomes to boundary conditions.

Improvement and Challenges

The past two decades have witnessed an expansion and improvement of our understanding of land change dynamics and our ability to project changes into the near-term future through many types of LCMs, especially those drawing on remote sensing data of land cover (as opposed to land use) and directed to changes in the biophysical dynamics of land systems (Agarwal et al., 2002; Lambin, 1997; Parker et al., 2003). Models have improved in their ability to treat spatial, temporal and decision-making complexity as described by Agarwal (2002) and render detailed outputs, from spatial scales of 1 m to 500 km. Model performance is linked to both the quality and resolution of the data employed and the degree of fidelity in representing the processes of land change. Machine learning, data mining, and statistical methods have advanced to improve our ability to identify patterns in the changes we observe. Economic modelers have taken advantage of spatially explicit data sets to build and improve models with varying levels of detail on economic decision making. Agent-based models have increased our capacity to address different types of agents (e.g., households, land managers) and their behaviors, especially when backed by empirical data about that behavior (Manson and Evans, 2007). Creative approaches have been developed for integrating LCMs across scales, across different approaches, and to other types of models, including biophysical and socioeconomic types.

These advances notwithstanding, LCMs confront a number of limitations that stem from both data constraints and limits to our understanding of underlying processes. Data constraints can be characterized in several ways, including limitations due to the sensor or source (e.g., spatial, spectral, and temporal resolutions), limitations due to development of model inputs from the raw data (e.g., lack of a single ontology for land use, land cover, or other land variables that can be used for classification across all applications), and limitations due to poor coordination of or restricted access to a variety of public and proprietary primary data about the land systems. Process representations are confounded by their complexity, and by temporal nonstationarity in land change processes (e.g., changes in zoning, policy, or environmental conditions), prompting an emphasis on near-term projections and highlighting the possibility that there are very real limits to the level of prediction we can expect LCMs to exhibit (Batty and Torrens 2005). In particular, the further into the future that model outputs are projected or forecast, the greater is the uncertainty of those outputs. In addition, feedback mechanisms within land systems are commonly not represented well, a shortcoming of increasing significance as LCMs address trade-offs of ecosystem services and their socioeconomic consequences. Perhaps most importantly, models are only beginning to account for spatial and social interactions among different land units, land users, and the environmental processes linked to them, especially as affected by the shape and pattern of land units and the network structures of social interactions. Finally, only a few models attempt to treat cross-scale dynamics—ascending or descending spatiotemporal scales of land use and cover and land change processes—rather than treating adjacent scales as boundary conditions.

KEY CONCEPTS

This report relies on and refers to a number of key concepts that underlie our understanding of both LCMs and the problems LCMs are built to address. Here, we address two major categories of topics, organized around the ideas of pattern and process, and of projection, forecast, and scenario, and define a number of key terms (Box 1.1).

Pattern and Process

Data on land change provide information about patterns that can be described over space and/or time. These patterns of composition and configuration are based on observations of various state variables in the land system (e.g., land use, land cover, land value, and land management). Spatial patterns can be described in the form of maps, or in quantitative measures derived from maps that characterize the organization or configuration of objects or values in the map. In land change contexts, this often involves characterizing the size, shape, distribution, and connectivity or continuity of land cover or land use, attributes that can have significant impacts on human-environment systems (e.g., Chan et al., 2006; Laurence and Williamson, 2001; McGarigal et al., 2012). Temporal patterns can describe changes in the composition and configuration of land over time and can be described graphically as time trends or with derived statistics that characterize the changes, trends, or variability over time. For example, forest transitions, involving loss and then regrowth of forest area within countries, exhibit a regular temporal pattern that some in the land change community have sought to explain (e.g., Rudel, 1998, 2005).

To explain observed land change patterns or trends, land change science seeks to understand *process*. This understanding can be represented with degrees of formality varying from informal conceptual models to formal mathematical or computational models. Stochastic aspects of this understanding might be included with otherwise deterministic processes to represent uncertainty and statistical variability in system behavior.

BOX 1.1

Terminology and Definitions

Boundary conditions – attributes and processes affecting the dynamics within a model that are set from outside the model and are not affected by dynamics within the model.

Calibration – parameters are set in a way that a model reproduces outcomes similar to those observed for the specific time and place of a case study.

Diagnosis – developing a degree of trust in the model through verification, calibration, and validation.

Drivers – variables that influence a land change variable (outcome).

Endogenous and exogenous variables – factors that are generated or determined from within a system (endogenous) or outside a system (exogenous) and can be developed within or outside a model, though they often change over time and/or space.

Equifinality – the principle that an observed pattern can be generated by multiple different processes.

Land change – change in land surface characteristics that are usually instigated by human action and that have consequences for environmental system functions.

Land cover – the biophysical qualities of the land surface (e.g., impervious surfaces, vegetation, water, bare soil).

Land system – a set of biophysical processes and human actors and organizations, together with the interactions among them, expressed spatially in the form of a mosaic of land units with different kinds and degrees of land uses and land covers.

Land use – the human intent given to or activity carried out on the land surface (e.g., housing, parks, and cultivation).

Linked, nested, and coupled models – linked model refers to one model result (process) affecting another; nested models are linked models arranged hierarchically by scale; and coupled models allow models to interact dynamically and often in two directions.

Outcome validation – comparison of model outcomes to data from a specific real-world case on those same outcomes.

Path dependence – ultimate or later outcomes of dynamic processes are dependent on the outcomes of earlier iterations of the process. Early outcomes can constrain the choices later on in the process.

Pattern versus process – patterns are descriptions of observed phenomena over some time interval or spatial area, whereas processes are the mechanisms that generate observed patterns.

Projection, forecast, prediction, and scenario – projection refers to a description of a future land system and pathway leading to it; forecast or prediction to the most likely projection; and scenario to a plausible description of a possible future state of a land system.

Scale – the extent and resolution of a variable or model in time, space, thematic categories, or organizations.

Scale dynamics – the process interactions across spatiotemporal-organizational scale.

Spatial interactions – the relationships between variables and processes across geographical locations, often described as pairwise relationships or spatial patterns.

Spatially explicit model – a model in which the data and outputs are specified for some set of geographical locations (e.g., from pixels to regions or continents).

Stationarity – processes during one time period or in one location are the same as those in the subsequent time period or other locations (antonym: nonstationarity).

Structural validation – evidence that the processes in a model accurately reflect those operating in a specific real-world situation.

Verification (debugging) – demonstration that the model's code expresses the intention of the modeler.

These distinctions are important because modeling approaches have been developed to support science and decision making in land change for a variety of reasons. Two broad purposes of models are to predict/project (PP) and to explain/learn (EL). While the two categories of purposes need not be mutually exclusive, PP can be carried out without the goal of gaining insight into fundamental system behavior that is the aim of EL.

Likewise, it is possible to use models for EL in ways that do not provide particularly strong PP capabilities. Models that use different structures or parameter values may fit observed data equally well, a circumstance referred to as *equifinality* (Beven and Freer, 2001). A model can provide a good fit to data for the wrong or unknown reasons, however, and not capture the internal form and processes of the real world. The ability to distinguish between model forms with similar degrees of fit is termed *identifiability*, which is constrained by the adequacy of observations, in terms of both accuracy and range of system properties. Where processes are represented dynamically, the same model configuration can produce potentially very different outcomes (a circumstance referred to as *multifinality*) depending on variations in boundary conditions or stochasticity in the parameters or processes, further challenging attempts at identification.

Modeling approaches range from inductive (or pattern based) to deductive (process based) (Overmars et al., 2007), though in practice these approaches are commonly used together in an iterative manner. Inductive approaches seek to observe relationships between outcomes and drivers in order to infer some process-level understanding from the patterns in data about specific cases. Deductive approaches, on the other hand, present models of general processes to specific cases or experiments that can be used to test these general explanations. These approaches can be used jointly in a form of abduction (Paavalo, 2004), in which results from analyses of pattern suggest a set of possible explanations that can be tested, the findings of which are fed back into the pattern analysis, often creating a chain of linked explanations for the phenomenon in question. In fact, most operational models reside somewhere between induction (i.e., pattern based) and deduction (i.e., process based). Where models fall on this continuum affects their characteristics and how their results can be interpreted by users. For example, a completely inductive approach uses no theory or thesis in developing the model structure and might rely instead on machine learning to establish relationships between driving variables and outcomes. (Even these approaches, however, require selection of the variables, which necessarily draws on some level of theory and process understanding.) This might limit the types of policies the model can be used to evaluate to those involving only changes in the input patterns, restricting their use for policies involving changes in process (e.g., incentives to the users of land to make different choices). On the other hand, a more strictly process-based model developed without recourse to data on (a) specific case(s) might have rich structural detail about the mechanisms but might perform poorly when it comes to reproduction of the observed patterns in data. Trading off these various strengths is an important component of model choice.

Projection, Forecast, and Scenario

Our statement of task highlights "future needs for higher-resolution and more accurate projections." Various research communities use the term projection—and affiliated terms, forecast and scenario—in different ways. In this report, we follow the definitions set out by the Intergovernmental Panel on Climate Change (IPCC).

The IPCC Third Assessment Report (2001) identifies a projection as "any description of the future and the pathway leading to it." For our purposes, projections can be derived from a LCM (e.g., future land use), although other input sources for such projections could exist (e.g., assumptions about land policies and economic activity). The IPCC distinguishes projections from forecasts or predictions (terms that are used interchangeably) by defining the latter two as projections that are branded as "most likely," often based on models to which some level of confidence can be attached.

In contrast, the IPCC defines a scenario as "a coherent, internally consistent, and plausible description of a possible future state of the world" (IPCC, 1994). Scenarios are used to make projections, but under a specific set of assumptions that can include projections from other models (e.g., economic forecasts). The uncertainties about these projections may be unknown, but they may represent plausible directions for the initial conditions and external driving forces for a set of processes (e.g., land change) (IPCC, 2000). Usually any set of scenarios will include a baseline against which others can be compared, often related to projections based on currently known conditions and processes. Scenarios can be exploratory, and describe how the future might unfold under a set of known processes or current trends, or normative, in that they describe a future that might be achieved (or avoided) if a specific set of actions is taken. The IPCC SRES scenarios (IPCC, 2000) follow the exploratory approach, based on a set of demographic and economic assumptions, whereas the representative concentration pathways follow a more normative approach, wherein they are defined with respect to the outcomes and used to evaluate ways those outcomes might be achieved (Moss et al., 2010).

NEEDS FOR SCIENCE AND PRACTICE

LCMs are used widely in the overlapping arenas of science and practice (decision making, policy, or real-world application in the private and public domains), and a clear understanding of the different requirements of each of these communities as well as their close connection provide context for the later sections of this report. In general, science is concerned with generating and organizing knowledge, and the field of land change science and related disciplines build LCMs to formalize and test land change and associated theory and explore scenarios where real-world experimentation is not possible. For the most part, science-driven modeling efforts tend to become more process based as understanding of a problem and the processes evolve, beginning with data-based exploratory models and proceeding toward more explicit representations of process in the models. The value of different approaches to LCM in science varies according to both the nature of the modeling approaches and the nature and specificity of the questions.

The communities engaged in practice are concerned with setting sound and defensible guidelines for policy and action, and LCMs provide value by revealing current and exploring possible future outcomes from policy or action. Given the number and range of different decision-making units charged with different facets of human-environment systems (e.g., climate or water regulation, housing or zoning, and corporations), LCMs often focus on or link to the missions of the individual practitioner groups. In consideration of the roles of models in decision making, Figure 1.1 provides a useful conceptual model of how decision making proceeds (Verdung, 1997) and serves as a touchstone for later discussions about the relative value of different modeling approaches at different stages in the decision process.

Problems (e.g., flooding) about which decisions and actions are needed are identified in a variety of ways and various interventions are designed to mitigate or reduce the problem. Upon evaluation of alternative interventions, some decision is reached and an intervention implemented. Following implementation, the intervention is evaluated and the results fed back into identifications of similar problems in the future. Models can contribute at each stage of this idealized process, but the information requirements are different at each stage.

Viewing LCMs in the context of the policy cycle will allow managers and policy makers to make more informed decisions regarding the type of model output needed during each phase of policy making. Framing LCM's in terms of the user needs rather than modeler interests represents a departure from previous LCM reviews.

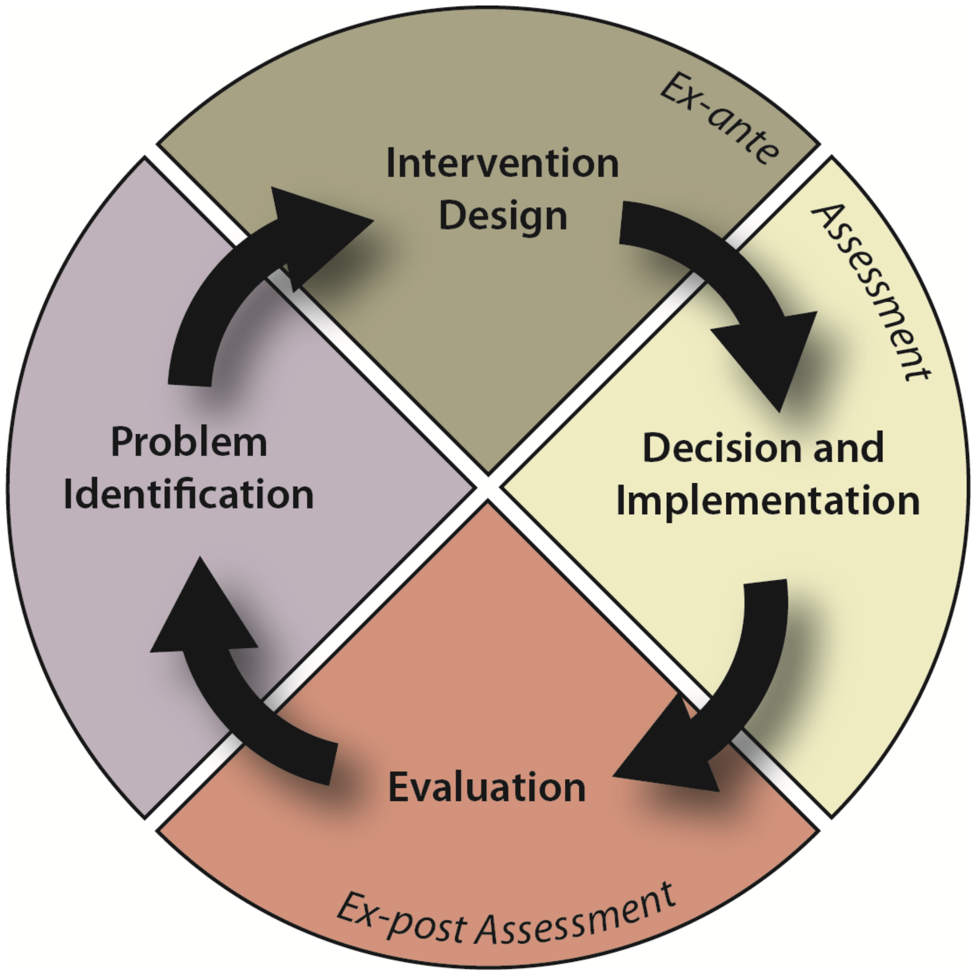


Figure 1.1. Decision-making process. SOURCE: Verdung, 1997.

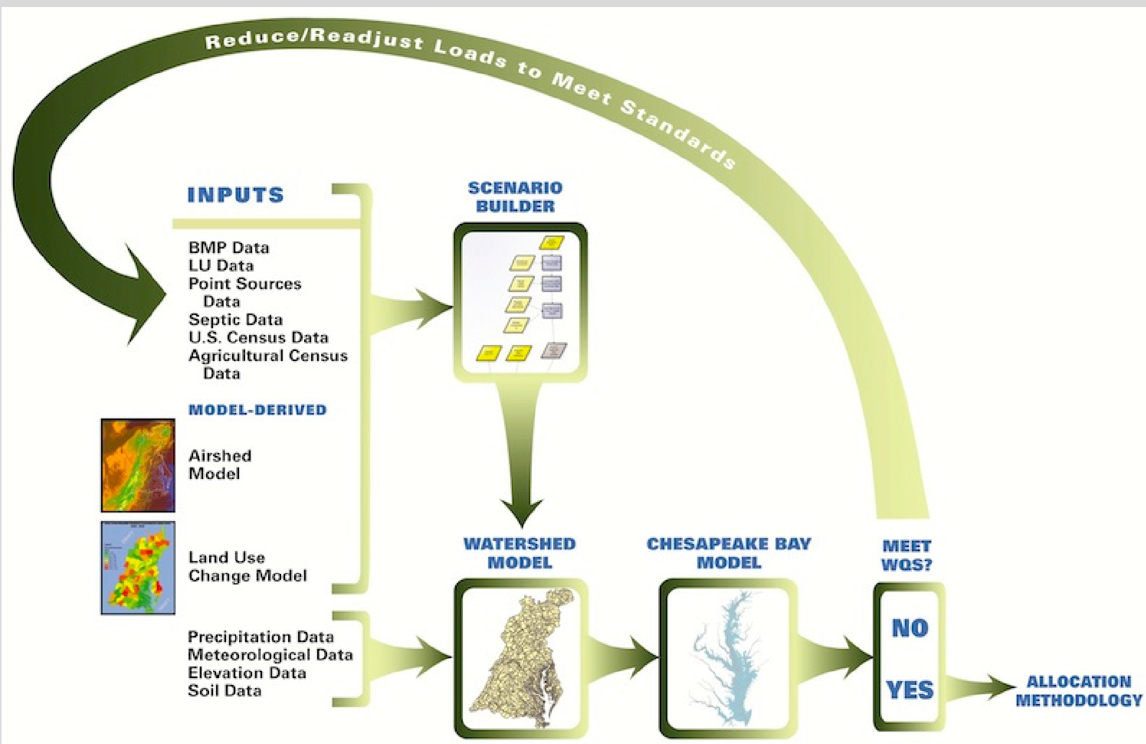
The Chesapeake Bay study provides an example of a context within which LCMs contribute to formulation of policy and management decisions through coupling with other environmental models (Box. 1.2). Land cover changes affect runoff and nutrient loadings, and can be adjusted in scenarios to evaluate the effects of alternative land-related patterns on achieving water quality goals.

A variety of science and policy communities, including climate change modelers, integrated assessment modelers, and the IPCC, are asking for better information about land change at global scales. Spatial LCMs would provide platforms for exploring future scenarios of rural-urban form and structure to support decisions about these mitigation strategies. Similar effects of spatial patterns on ecological and biogeochemical processes have demonstrated a need for spatially explicit characterizations of land change (Debinski and Holt, 2000; Irwin and Bockstael, 2007; Robinson et al., 2007).

BOX 1.2

Chesapeake Bay Land Change Model as Input to the Chesapeake Bay Watershed Model

The Chesapeake Bay Program (CBP) is a consortium of federal agencies, states, and Washington, D.C., that aims to develop strategies and implement methods to restore the health of the Chesapeake Bay. A key component of the CBP is the use of an LCM, based on SLEUTH, to provide scenarios of land use and land cover that can be input to the Chesapeake Bay Watershed Model. Current and future scenarios of land change are entered as input to the CBP Scenario Builder to develop parameter sets to parameterize the watershed model for simulation of stream flow, nitrogen, phosphorus, and sediment loading to the Bay. Different scenarios for land use change are developed to assess the long-term potential of achieving water quality goals and to help set policies on development and watershed to local-level restoration methods.



SOURCE: Image from website: http://www.chesapeakebay.net/groups/group/modeling_team.

Despite the differences noted among the uses of LCMs, the science and practice communities are connected bidirectionally in the same way that humans and the environment are connected. Science informs policy and practice, and the outcomes or needs of the latter often prompt additional scientific research. Such feedbacks are instrumental to the advancement of LCMs.

MODEL UNCERTAINTY

We note above that temporal non-stationarity in land change processes creates uncertainty in LCM projections, especially the further into the future that the model is applied. In addition, an important property of all models is that they contain some irreducible level of uncertainty that can be inherent in the model structure (i.e., the basic equations or algorithms), the parameter values, input data, or all of these. Uncertainty is endemic in our understanding of land use decision making and of the physical state and function of the land system.

The future state of land systems will be determined by a combination of individual and societal constraints and opportunities about which decisions have yet to be made. LCMs implicitly or explicitly address decision making in the face of opportunities and constraints and biophysical processes not subject to human decision making, but which may be fundamentally affected by it. For example, a model can simulate where humans will change the landscape, a decision-making component that is inherently uncertain. Other parts of the model follow physical principles that may not change but are subject to data and parameter uncertainty. For instance, models that connect land change with the storage and movement of water are guided by physical laws of hydraulics. Incomplete knowledge in the current state of water infrastructure, surface topography, and subsurface structure, however, introduces substantial uncertainty into understanding and prediction of fundamental physical processes. In addition, decision-making processes and physical processes interact in a model, for example, as humans change landscapes by installing or retrofitting drainage infrastructure toward specific water management goals, which can change over time (Huang et al., 2013). This provides strong feedbacks to land, to the biological and geophysical properties of the landscape, and to human decision making, which may need to be incorporated into a LCM. In some instances, human use of the land can drive the environment to thresholds that, once crossed, change environmental (ecosystem) function (DeFries et al., 2004) and amplify uncertainty.

Model diagnosis, a fundamental part of any modeling exercise, seeks to learn about the behavior of the model relative to the real system in order to interpret model output appropriately. This diagnosis accounts for the essential modeling steps of verification, calibration, and validation. When model parameters are fit by calibration to historical data, additional uncertainty is introduced due to the inherent temporal nonstationarity of processes. Model diagnosis must, therefore, also account for nonstationarity in the data and processes, and stationarity assumptions in the model. Model diagnosis is critical to evaluating the representation of interacting processes, the manner in which the landscape is represented, and the uncertainty in each of these forms. In Chapter 3 we outline a framework for best practices in model diagnosis in the context of LCMs.

MEASUREMENT AND CHARACTERIZATION OF LAND CHANGE

Land change modeling confronts a rapidly changing data infrastructure that affords large opportunities for improved models and their application, but it also entails a number of important issues about data quality and assessment that require consideration during model development and testing. These include issues related to remote sensing of land change as well as other data on the various social and biophysical characteristics that define the land system and its drivers within LCMs.

Remote Sensing of Land Change

The science of characterizing and measuring land change from remote sensing data has evolved significantly over the past 40 years. The earliest methods—and still widely used—identify land change as the difference between classified land cover maps from two or more points in time or through direct detection of changes themselves based on one or more images (Coppin et al., 2004). Although this remains the most common approach to characterize land change due to its simplicity and flexibility, it is more appropriate for identifying coarse-scale quantitative changes based on specific points in time (e.g., deforestation, urban expansion) than it is for identifying nuanced qualitative changes (e.g., changes in urban density, vegetation health) or dynamic processes that evolve over time, like crop rotation and change.

Advances in change detection analysis provide new opportunities for LCM. Most notably, new algorithms that use the entire set (or a subset) of the long archival record of many sensors, such as Landsat or MODIS, take advantage of the temporal signal to identify land changes not possible through the traditional differencing approach (Zhu et al., 2012). New methods developed from allied fields such as geostatistics (Kaliraj et al., 2012), artificial intelligence (Ghosh et al., 2008), and time-series analysis (Verbesselt et al., 2010) further improve and expand the type of information that can be extracted from remote sensing data. Moreover, change detection methods are moving away from individual pixel analysis and incorporating spatial neighbors and shape. Further, a whole community has emerged around the use of objects as the unit of analysis in object-based image analysis and change detection (Chen et al., 2012). Many of these new algorithms and methods have yet to be fully utilized in LCMs.

Here we briefly take stock of some of the key advances in remote sensing that significantly contribute to the development of LCMs. In Chapter 3, we identify new challenges for remote sensing for LCMs and emerging developments in algorithms and image processing that could meet these challenges.

1. The growing depth of the Landsat archive, coupled with the no-cost policy governing its access, has driven a lot of efforts to model observed changes. This data set can be seen as an important impetus and enabler of the current state-of-the-science in LCM.
2. The growing constellation of private and government sensors offer a wide range of spatial resolutions, from submeter (Pleides, Quickbird, WorldView, GeoEye) to 250-500 m (MODIS). Revisit frequency from daily to weekly observations makes it

possible to examine land change with high temporal frequency. With archival records from Landsat, long time series are being coupled with high-temporal-frequency and high-spatial-resolution analyses. This increased temporal frequency improves our ability to characterize dynamics in the land system, diagnose temporal nonstationarity, and develop empirical parameter sets for LCMs that are better tuned to historical changes.

3. Data from land imaging sensors cover a wide spectral range, from the visible to the long-wavelength infrared (also known as thermal imaging) and with different spectral bandwidths. Combined with the trend toward higher radiometric resolution with dynamic ranges up to 16 bit (65,536 unique values per pixel per spectral band), the land change community now has available a large range of high spectral detail in a single pixel. This helps to refine the detail within which land attributes and types can be represented, and it opens the possibility of incorporating more thematic detail into LCMs.
4. There are growing numbers of algorithms for spectral mixture analysis to estimate the fractions of different materials or cover-types within mixed pixels. Rather than assuming a single land cover type per pixel, the resulting maps provide continuous fields that represent fractional cover of different categories and that could be the targeted outcome represented in future LCMs.
5. Algorithm developments that move away from pixel-based analysis provide new looks at landscapes using shapes and objects as the unit of analysis. Outputs from these analyses are particularly useful for identifying human activity or management of the landscape (e.g., agricultural plots) and hold the potential to interact more directly with models of human decision making.
6. Multiple LiDAR remote sensing platforms, from spaceborne to airborne systems, provide information in the third dimension. For example, the Geoscience Laser Altimeter System on ICESat collected data that can be used to map vegetation canopy parameters including tree height, biomass volume, and stand density. Sensors of this sort further expand the land variables that can be sensed and included in LCMs, either as inputs or outputs.

Whereas for many years, the primary land imaging sensors were Landsat and the Advanced Very High Resolution Radiometer, the LCM community now has at its disposal a large range of additional sensors and types of information for LCM inputs. As discussed in Chapter 3, however, the community is only beginning to harness the synergies possible from algorithm advances in both the LCM and remote sensing communities.

Other Data for Land Change Models

In addition to data from remote sensing, data from a wide variety of other sources are central to development of the ability in LCMs to both characterize aspects of the land system that cannot be directly observed with Earth observation technology (e.g., property ownership) and incorporate information about the social, historical, ecological, and other drivers of land change (e.g., population growth, economic activity).

A common challenge that arises with using these data for LCMs is that, with the exception of customized surveys, none were designed explicitly for use in LCMs but rather for different audiences and different purposes. For example, census data are collected over various administrative units and usually at decadal intervals. In addition, they can usually be used only at some aggregate level (e.g., census blocks), not at their finest spatial resolution. Other data may be recorded or collected more intermittently. Land values, for example, may be updated only when a property changes ownership. Four measurement and characterization issues common to all data for LCMs are briefly reviewed below and opportunities for future advancement are outlined in Chapter 3.

Format of variables

The subjective decision to format variables in LCMs as *continuous* or *discrete* influences the type of questions that can be answered and the type of analyses that can be employed (Southworth et al., 2004). With discrete variables, each spatial unit is represented by a single categorical value, and these data can detect wholesale changes in either the land use or cover (e.g., agriculture to urban) or the input drivers (e.g., change in land ownership). Continuous variables allow measurement and characterization of finer details, such as qualitative changes in land use or cover (e.g., agricultural intensification or variations in net primary productivity) or modification in driver variables (e.g., changes in agricultural inputs such as fertilizers). The use of crisp categories simplifies analysis, but it requires that the number of categories to use must be determined and categories must be applied consistently over time. More categories add more detail, but they also make the analysis more complicated. It can be desirable to aggregate categories to reduce the data to a small number of important categories; the manner in which aggregation is performed influences the signals of land change.

Data accuracy and reliability

Understanding the accuracy and reliability of the data used in LCMs is essential. With remotely sensed data, accuracy is affected by the data source (i.e., sensor) and by the processing steps involved in creating the final map. The lineages of other LCM data are often more difficult to identify. For example, the specific instruments, field methods, original source material, or analyses used may not be recorded or evident. Consequently, it is often difficult to assess the accuracy or reliability of these other data sources. Additionally, the increasing availability of "volunteered geographic information" (Goodchild, 2007), for which individual citizens provide geographic information, presents a new trove of information for observing and analyzing change (NRC, 2010c). While the accuracy of these data is nearly impossible to assess, especially given the magnitude of the information available and the lack of strict protocols in its collection, the volume of data can often be used in creative ways to develop robust characterizations of the phenomenon of interest.

Multiple time points

Inherent to all LCMs is information over time. New methods are needed to consider the use of data with high temporal frequency in LCMs (de Beurs and Henebry, 2005). While the availability of temporal data from coarse-resolution imagery (i.e., > 100 m resolution) has been common for a couple decades, the availability of high-frequency data with finer resolutions (i.e., <50 m resolution) is a recent occurrence. A challenge for other data sources, such as field surveys and censuses, is how to sustain consistent collection efforts over the long term to create time-series data that could be more useful for LCMs.

An Abundance of New Data Sources

The growth of new data sources from satellites, aircraft, ground sensors, and "citizen science" presents new opportunities to measure and characterize land systems. The massive increase in data-gathering methods and data sets has not been matched by parallel increases in approaches for turning raw geographic data into more meaningful information about land systems or inputs to LCMs. The increase in information that describes and measures land systems requires expertise in inference and knowledge of the local systems in order to make effective use of it. In other words, new skills are required to synthesize and qualify data from multiple sources and disciplines. Furthermore, measurements from different agencies, sensors, and researchers may share the same or similar categories but under significantly different conditions and assumptions (i.e., the semantics are different)—a common problem in integrating land classes undertaken by different research programs. Therefore, LCMs cannot simply integrate these data into a single database; land change scientists must identify robust approaches to translate the raw observations into meaningful information (Di Gregorio, 2005).

STRUCTURE OF THE REPORT

Land change models have been and continue to be critical to a large range of uses and users in science and practice. Indeed, the demands on LCMs continue to increase in terms of product outcomes and uses. These demands confront a series of problems, the broad outline of which has been noted. Input to inform the opportunities identified in this report was gathered at committee meetings and a workshop, through the committee's own expertise, and through a questionnaire distributed electronically to a variety of individuals and groups working on LCMs (see Appendix A for a full list of contributors). The workshop included national and international experts in land-climate interactions, water quantity and quality, food-fiber, energy, ecosystem services, and urbanization. In Chapter 2 we describe and compare approaches to LCM and suggest guidance for their appropriate application. In Chapter 3 we suggest ways to improve LCMs and outline several forward-looking issues.

2

Land Change Modeling Approaches

To move land change modeling forward, it is critical that a common language is established to differentiate modeling approaches according to their theoretical and empirical bases. The diversity of approaches to land change modeling, along with differences in definitions between practitioners from different disciplines, does not lend itself to a discrete classification system. Agarwal et al. (2002) described models in terms of how they handle spatial, temporal and decision making complexity. While this approach provided useful distinctions at the time that review was completed, significant progress in developing all modeling approaches has blurred even some of those distinctions.

The committee has identified six generally recognized groups of approaches to land change models (LCMs), the first five of which are arrayed roughly in order from least to most structurally oriented (i.e., focused on process): (1) machine learning and statistical, (2) cellular, (3) sector-based economic, (4) spatially disaggregated economic, (5) agent-based, and (6) hybrid approaches. While we mention statistical approaches in the first category explicitly, statistical methods are used in some way within most of the approaches. There are overlaps in the degree and type of process orientation among the approaches that depend on the details of the specific model representing these approaches. We include the sixth type to acknowledge the importance of studies and applications that combine the different approaches into a single model or modeling framework. The following sections outline the theoretical and empirical bases as well as technical, research, and data challenges for each approach. Examples of each approach are also provided. Because of similarities in the approaches, we address both forms of economic models in a combined section. Following the discussion of each approach, we compare the key assumptions, data requirements, and recommended uses of each modeling approach.

MACHINE LEARNING AND STATISTICAL

Theoretical and Empirical Basis

Machine learning and statistical methods in LCMs involve approaches to represent relationships between inputs (i.e., driving variables) and outputs (i.e., land use or cover changes). The data are used to generate maps of transition potentials that give an empirically based measure of the possibility of particular land transitions. Together with traditional parametric approaches, usually in the form of logistic regression (Millington et al. 2007), generalized linear modeling, or generalized additive modeling (Brown et al. 2002), several different kinds of Bayesian and machine learning algorithms have been used in influential LCMs. For example, the Dinamica model offers the option of logistic regression or a weights-of-evidence approach, which estimates a statistical model similar to logistic regression, but does so within a Bayesian framework (Carlson et al. 2012).

Neural networks play a central role in both the Land Transformation Model (Pijanowski et al., 2002; Ray and Pijanowski, 2010; Tayyebi et al., in press) and *Idrisi*'s Land Change Modeler (Eastman, 2007). Neural networks represent relationships between land transitions and their explanatory variables through a network of weighted relationships that the algorithm adjusts iteratively. Genetic algorithms (GAs) have been used to optimize the rule set for cellular automaton models, by iteratively adjusting the parameter string that defines weights on variables (Jenerette and Wu, 2001). The SLEUTH model (Clarke, 2008) uses an input-assisted incremental approach to calibrate a cellular automata model, but attempts have been made to use genetic algorithms for this purpose (Goldstein 2004). Classification and regression trees are data mining tools that use a sequential partitioning process and have been used to model the probabilities of landscape change (McDonald and Urban, 2006). A comparison across approaches that included logistic regression, Bayesian analysis, weights of evidence, and a neural network showed a case-study site where the neural network produced a more accurate prediction during a validation interval as measured by the area under the relative operating characteristic (ROC) curve and a Pierce skill score (Eastman et al., 2005). Although we do not review all of the individual methods in detail, we describe the strengths and weaknesses of this overall approach relative to the other modeling approaches covered in this study.

Modeling approaches that employ a machine learning or statistical approaches typically receive input in the form of two types of maps: (1) maps of land cover at time points that bound the *calibration interval*, and (2) maps of explanatory variables, such as topographic slope, distance to roads, etc. After the algorithm finds this relationship for the calibration interval, the relationship is then typically used to extrapolate the same relationship into a subsequent *validation interval* during which the predictive power can be tested. Machine learning algorithms can be appropriate for situations where data concerning pattern are available and theory concerning process is scant. There are many cases where it is possible to obtain land cover maps from more than one time point along with explanatory variables for a study site where the investigator is partially ignorant concerning the detailed processes of land transformation. A machine learning algorithm attempts to learn the mathematical or logical relationships among the patterns of land cover and the patterns of the explanatory variables. The machine learning algorithm focuses exclusively on encoding and extrapolating the pattern of the land change, as opposed to the process of change. If the approach is used for prediction, then the prediction assumes stationarity in the land change pattern from the calibration interval to the subsequent time interval. Machine learning algorithms are used to predict by extrapolating historic patterns and can perform the extrapolation in a manner that does not require theory concerning detailed processes of change.

Machine learning algorithms are not designed to simulate feedbacks and nonstationary processes in coupled natural and human systems, nor are they designed to evaluate the effects of policies that attempt to modify processes so that future patterns will be different than the past patterns. Machine learning algorithms are not designed to simulate the mechanisms of human decision making, because machine learning algorithms lack theory concerning the behavior of decision making.

Statistical regression methods assume a fixed mathematical form with coefficients that an algorithm estimates to produce an optimal fit, where optimal is defined by a mathematical criterion, i.e., a maximum-likelihood criterion. The maximum-likelihood criterion leads to a mathematical formula to estimate the regression's coefficients. For example, the regression equation could assume a monotonic sigmoidal relationship between land cover change and topographic slope. Then the maximum-likelihood algorithm estimates the equation's coefficients so the regression curve fits as closely as possible to the data, given the form of the monotonic sigmoidal relationship. The coefficients indicate whether the assumed monotonic relationships are increasing or decreasing, and at what rate. The logistic regression might also include interactions among the explanatory variables. Diagnostic measurements help to interpret the fitted coefficients of the regression equation.

In comparison with logistic regression, machine learning algorithms do not require strong assumptions concerning a particular form of a mathematical equation to express a relationship between the land cover map(s) and the map(s) of explanatory variable(s). Machine learning algorithms attempt to mimic biological learning systems through predictive artificial intelligence tools. They fit a relationship between the land change variable and the explanatory variable(s) in a manner that is more flexible than regression concerning the mathematical structure of the fitted relationship and can be designed to be more robust to errors in the data (Bishop, 1995). The algorithm uses an iterative process to fit a relationship between the patterns in the land cover maps and the explanatory variables. Over repeated iterations, the algorithm adjusts the model parameters until the algorithm satisfies a stopping criterion. The stopping criterion signals that the algorithm either has generated a particular degree of fit for the relationship between the land cover maps and the explanatory variables, or a particular amount of stability in the fit from iteration to iteration.

Machine learning algorithms do not necessarily assume sigmoidal or monotonic relationships between the likelihood of land change and explanatory variable(s). The machine learning algorithms can also fit interactions among variables, just as regressions can. Machine learning algorithms are similar to common statistical approaches, in the respect that theory concerning processes of land change is expressed through the selection of explanatory variables to include and their expected relationships and functional forms, though the theory does not necessarily need to be rich. Many models base selection of variables on the von Thünen idea of land rents, which relates land use, cover, and change to location relative to markets and transportation as well as land suitability through variables like soil quality and slope. This theoretical basis is shared with many cellular models, and is described in more detail in that section.

Machine learning and statistical approaches can be appropriate for situations where data concerning pattern are available and theory concerning process is scant. In terms of short-term PP uses of models, machine learning approaches can be used to make useful predictions. There are many cases where it is possible to obtain land cover maps from more than one time point along with explanatory variables for a study site where the investigator is partially ignorant concerning the detailed processes of land transformation. A machine learning algorithm can be used to first identify and represent patterns in data, relating inputs (predictor variables) and outputs (a land or land change variable) then generalize those relationships to other data sets. As more data become available for LCM applications, the ability of machine learning algorithms, in particular, to represent and generalize relationships in those data offers significant potential for dealing efficiently with large data volumes.

Technical, Research and Data Challenges

Because the methods and resulting modeled relationships involved in both machine learning and statistical approaches are developed inductively on the basis of the inputted data, the models are particularly sensitive to the inputs. For example, statistical or machine learning models can be applied to model either land use or land cover, and the categories used in the classification will determine the resulting model form. The meaning of the model is determined by the definitions of these categories. Therefore, model suitability for a given purpose will be dependent on the categories in the input map. For these reasons, and because land cover data are more plentiful than land use data, statistical and machine learning approaches are suitable for modeling land cover changes directly, even though these changes may come about through human choices about land use. While machine learning methods have been developed in ways that make them less sensitive to random errors in the input data than statistical methods, systematic biases in data will always affect the resulting models.

Used in a predictive mode, both machine learning and statistical approaches generally assume stationarity in the relationship between predictor and land change variables, i.e., that the model fitted during the calibration interval can be applied to the subsequent time interval without modification. The advantage is that these approaches can be used to predict by extrapolating historic patterns, and can perform the extrapolation in a manner that does not require theory concerning detailed processes of change. Additionally, any variables included as predictors in the model can be modified to generate scenarios of future change. For example, if distance to roads is a predictor variable it is a relatively simple task to simulate the effect of introducing a new road by recalculating distance to the nearest road. The disadvantage is that variables that are not included in the model, but that might change over time, cannot be accounted for in the projections or scenarios. What this often means is that scenarios involving changes to the economic penalties or incentives or other behaviorally related variables or constraints cannot be simulated. However, we address reduced-form econometric approaches in the section on Economic models, in which statistical methods can be used to estimate and evaluate behaviorally oriented scenarios.

Statistical and machine learning approaches differ in the degree of *a priori* structure imposed by the modeler, such that machine learning algorithms can more easily represent a variety of complex relationships but there exists a greater risk of overfitting. Overfitting can occur when an algorithm produces a mathematical or logical relationship between observed land change and a set of explanatory variables that fits the details of a particular calibration data set but does not apply to a broader set of applications. This can happen when the relationship fits the details of the calibration data in such a way that the model fails to represent the general principles that extend to other times or places. Spatial or temporal nonstationarity in the land change process can mean that a good fit at one time or place will not generalize well to other times or places. For example, a machine learning algorithm might be able to fit a tight relationship between land cover maps and explanatory variables for a given time interval but do a relatively poor job of matching observations when the relationship is extrapolated to time points beyond the calibration interval, for example because the market or policy conditions differ between the two time periods.

If the model is overfit during the calibration stage, then the investigator can be lured into a false sense of trust that the model can predict accurately the patterns in data for which the model was not calibrated. Overfitting can occur in nearly any modeling approach, especially approaches that calibrate a model based on a single case study. Thus, an important research topic concerns methods to measure and to address overfitting. Because this is a well-known problem in machine learning algorithms, a variety of techniques have been developed to reduce the risks of overfitting, and generalization outside the calibration data has been demonstrated for LCMs (Pijanowski et al. 2005). One approach that has not yet been tried with LCMs is to generate 100s or 1000s of models based on the stochastic elements of machine learning that can serve as a model ensemble and characterize a range of possible models for a given data set.

Interpretation of output can be challenging because many algorithms produce a map of "transition potential" for each land transition, where the transition potential indicates whether the apparent conditions are such that the chances of land change are relatively high versus low. The transition potentials are typically real values on the interval from 0 to 1, and have meaning in terms of their relative ranking, but are not necessarily probabilities of change because they are based on the time interval of change from the data on which they are based. A separate algorithm typically selects pixels with the highest-ranking transition potentials to make a hard classification of future change, where the number of selected pixels is based on an anticipated quantity of land change over some specified time interval. This situation makes it challenging to compare two or more maps of transition potential, since a map that has a higher average transition potential does not necessarily imply a higher anticipated quantity of change compared to a map that has a lower average transition potential. Even if two maps have the same average transition potential, it is not clear how to compare maps when they have differences in the distribution of the transition potentials, for example, when one distribution has a single mode but the other distribution does not. A transition potential can be interpreted as a probability when it indicates the chance that a particular categorical transition will occur in the pixel during a specific time interval. It is possible to convert some types of transition potentials to probabilities by scaling the transition potentials using a projected quantity of each categorical transition during a specific time interval (Hsieh, 2009). If transition potentials are probabilities, then they have an implied quantity of change for the specified time interval.

Compared to statistical methods, for which a large body of theory exists to facilitate diagnosing and interpreting the structure of a given model, machine learning approaches are often criticized as a 'black box' for which interpretation of the model structure and performance is a challenge. This is a well-known challenge for machine learning approaches, and a variety of methods have been developed to understand how the predictor variables relate to the outcome (e.g., to open the black box). For example, a simple approach to understanding the relative contribution of different variables to a machine learning model is to leave out each of the variables one at a time and re-calibrate the model (Pijanowski et al. 2002). Additionally, in terms of measuring how well the relative ranks from the model represent the spatial allocation of the observed transitions, The Relative Operating Characteristic (ROC) is frequently used because it is designed to measure the degree to which higher ranks are concentrated on the feature of interest (i.e., change). ROC has been criticized because many modelers use only a single summary statistic of the area under the ROC curve (AUC) to indicate association (Lobo et al., 2008). The AUC fails to expose the rich information that proper interpretation of the full ROC curve can reveal. Another criticism is that, like other metrics of predictive ability, the AUC can be large due to correctly predicted persistence, not correctly predicted change. This problem can be mitigated through careful selection of the study extent and by proper use and interpretation of the full ROC curve.

Modifications and alternatives to the ROC type of analysis can better express the manner in which a transition potential map fits the empirically observed land change. Proper selection of the measurement is important because the apparent performance of the algorithm can be sensitive to the selection of the measurement. For example, if the machine learning algorithm attempts to maximize the percentage of pixels that agree between the simulated map of land cover types and the reference map for the same time point, then the algorithm might generate output that systematically underestimates the quantity of change. This can occur because a simulation of land change is likely to generate allocation errors when it simulates change; thus, it can reduce the number of those allocation errors by simply predicting very little change. If instead the algorithm seeks to maximize a different measurement, such as the figure of merit (Pontius et al., 2008, 2011), then the algorithm has an incentive to simulate a more accurate quantity of change, because one must simulate an accurate quantity of change in order to have the possibility to generate a high figure of merit.

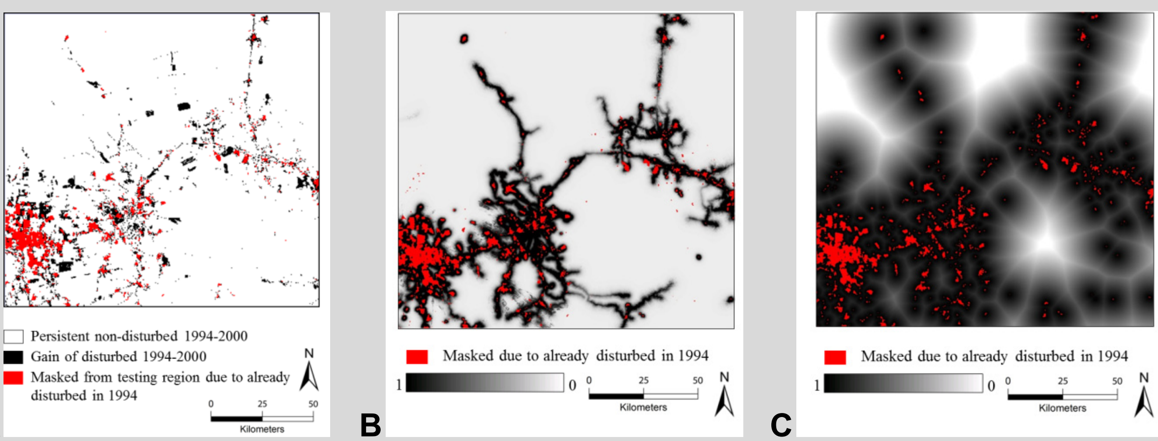
BOX 2.1

The Multi-Layer Perceptron

The Multi-Layer Perceptron (MLP) is a machine learning algorithm that is available as an option in the Land Change Modeler within the *Idrisi* GIS software. MLP is a neural network that receives maps of explanatory variables and land transitions for a calibration time interval and then produces a map of transition potential for temporal extrapolation beyond the calibration time interval. The transition potential is an index on a scale from 0 to 1, where higher numbers indicate pixels that have a combination of explanatory values that are more similar to places where the particular transition occurred during the calibration interval compared to places where the transition did not occur.

The maps below illustrate validation information using *Idrisi*'s tutorial data concerning the gain of disturbed land in Chiquitania, Bolivia. The MLP produced the transition potential map based on the gain of disturbance during a calibration interval (1986-1994) and explanatory variables including slope, elevation, and distance from streams, roads, urban areas, and previous disturbances. The validation interval is 1994-2000; thus, the disturbed pixels of 1994 are masked from the analysis because they are not candidates for post-1994 gain of disturbance. Map A shows the validation data, where black patches show a gain of disturbance. Map B is the output from the MLP, where darker shades indicate relatively higher transition potentials. Map C is a transition potential map that is based exclusively on proximity to disturbed pixels of 1994, where relatively higher transition potentials are assigned to pixels that are closer to disturbance of 1994. The proximity model is included because it is best practice to compare the map from a relatively naïve model to the output from a more complex model.

A B C



(A) Gain of disturbance during validation interval, (B) transition potential from *Idrisi*'s Multi-Layer Perceptron, and (C) transition potential from a naïve proximity model.

CELLULAR

Cellular land change models use discrete spatial units as the basic units of simulation. Such spatial units can be regularly shaped pixels, parcels, or other land units and are usually arrayed in a tessellation. Cellular models use a variety of input information to simulate the conversions of land cover or land use in these land units based on a rule set or algorithm that is applied synchronously to all spatial units and that represents the modeler's understanding of the land change process. The algorithm represents decision making that is, implicitly, assumed to take place at the level of the spatial units of simulation, with a one-to-one correspondence assumed between the spatial units and decision maker. Often, the same decision algorithm is applied to all spatial units in a study area, or to large regions within the study area. Variation in decision making can, therefore, solely arise from the attributes of the spatial unit, rather than from the differences in decision making of the actors managing the spatial units.

Theoretical and Empirical Basis

A wide variety of cellular models has emerged over the past two decades, differing in their specification and underlying theoretical and empirical basis. Differences between cellular model types relate to differences in the algorithms and the underlying assumptions that govern the decision rules at the level of spatial units. Another difference between groups of cellular models relates to the way the quantity of change is determined, as distinct from the locations of change. Modelers generally choose between either constraining the total areas of land change at the regional level or determining the regional level of land change simply as the aggregate of the changes at the level of individual spatial units (Figure 2.1). In this section we first look at the theoretical and empirical basis of the decision models. This is followed by a discussion of the top-down versus bottom-up guidance in determining the regional quantities of allocated land change.

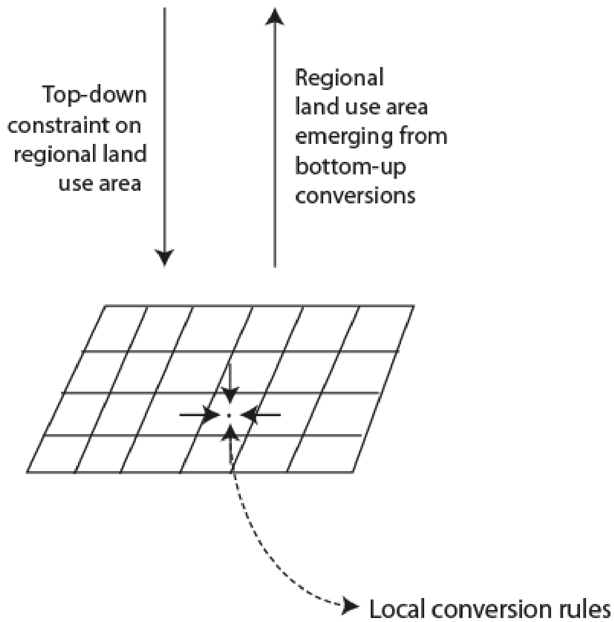


Figure 2.1 Different modeling approaches: Spatial allocation is constrained by a top-down demand or fully determined by local conversion rules.

An assortment of conversion rules have been applied within cellular models. However, the underlying assumptions can be categorized in three different groups based on the underlying theoretical basis of the models (Schrojenstein Lantman et al., 2011): (1) a continuation of historical trends and patterns, (2) allocation based on suitability of the land, and (3) allocation based on neighborhood interactions.

Continuation of Historical Trends and Patterns

The premise behind the use of historical trends to project future trends is that future land use is assumed to follow patterns of change corresponding to recent or historical changes. The use of this assumption may vary from simple application of transition probabilities from observed historic changes to the use of observed land changes over a past period to empirically estimate relationships between land change and location characteristics. This latter case is similar to the application of machine learning methods outlined in the previous section and is elaborated below in the discussion of land suitability. As an example, this may mean that if agricultural land use was found close to cities in the past, it is assumed that future predictions of agricultural land will be allocated close to cities. Implicitly, this assumes stationarity in the underlying decision making of the actors of land change. Often times this assumption is appropriate, but a better understanding of the specific model elements for which and conditions under which stationarity is a reasonable assumption would help with structural evaluation of models, a topic we revisit in Chapter 3.

The most well-known approach to constructing models based on continuation of historical trends is the use of Markov chains. In its basic application to land change, spatial data are used to calculate a transition matrix over an historic time period and then used to derive transition probabilities for the different types of conversions. These probabilities are used to calculate land areas of different land types in the future in a nonspatial manner. Burnham (1973) was one of the first to propose using Markov chain analyses for modeling land use change, but they were later applied by others (Muller and Middleton 1994; Fearnside; Turner 1987). Because of its simplicity, Markovian analysis was very popular during the early phase of development of land change models. However, the approach has a number of limitations. The primary limitations of Markov transition probability-based models for land use and land cover change analyses are (1) the assumption of stationarity in the transition matrix, that is, that it is constant in both time and space; (2) the assumption of spatial independence of transitions; and (3) the difficulty of ascribing causality within the model, that is, that transition probabilities are often derived empirically from multitemporal maps with no description of the process (Baker, 1989; Brown et al., 2000).

Several authors have tried to overcome some of these limitations by merging the Markovian concepts with other simulation rules and concepts; (Goigel and Turner, 1988; Guan et al., 2011. These hybrid models often use Markovian models to determine future quantities of change while the spatial patterns are simulated by another type of cellular model. Though many models have developed approaches other than Markov chains to describe future changes, the assumption of stationarity is common in other model types. Many statistical and econometric models of relations between land use and location factors assume that such relations remain valid for the period of simulation.

Suitability of Land

Many cellular models use, in one way or another, an assessment of the suitability of the spatial units for alternative land uses as a determinant of the conversion rules. The land suitability in cellular models is underpinned by the theoretical work of von Thünen (1966) and Alonso (1964), which explained land use allocation patterns based on the spatial variations in land rent for different land uses. Following on the premise that land users aim to maximize profit, each parcel is converted to the use with the highest land rent at that location. While land suitability is often represented only in a relative terms, these suitability models provide a basis for understanding where different land uses or covers are most likely to be found. Whether or not land rents are calculated in absolute or relative terms often depends on data availability, and relative land rents are commonly used for models of land cover, where there may not be a good theoretical link between economic rent and cover type. In the original specification of the von Thünen model, land rent differs by location and land use due to differences in transportation cost and distance to the market. Elaborations of these premises accounted for differences in soil quality and infrastructure (Alonso, 1964), while Walker and others (Walker, 2004;Walker and Solecki, 2004) extended the underlying bid-rent model to account for development and agency.

The suitability of the land is determined in different ways. In some models land suitability is directly derived from the physical suitability for alternative uses based on agroecological zoning assessments; in other instances this is represented by the potential crop yield that may be obtained (Schaldach et al., 2011). Other approaches also include infrastructural and socioeconomic location characteristics in the determination of the suitability for a particular use. The importance of different location factors as determinant of the suitability can be based on expert knowledge captured in multicriteria evaluation procedures (Schaldach et al., 2011), a statistical or machine learning approach (as described above), or econometric estimation based on current land use patterns, described below in the section on economic approaches (Chomitz and Gray, 1996; Nelson and Geoghegan, 2002; Verburg et al., 2004a). Multi-criteria evaluation methods do not make strict use of the rent-based framework of von Thünen, but provide a means of evaluating how changes in policy goals or preferences affect desired land allocations in a planning context (Eastman et al. 1995; Klosterman 1999). It is important to note that econometrically derived suitability maps include factors related to both physical suitability and the accessibility of locations and population pressure.

The implementation of suitability maps and their role in allocating land change differs between models. Differences mainly depend on the number of land use and land cover types addressed and the level of competition assumed among the categories. In its simplest form land change between two classes is simulated (e.g., urban vs. nonurban or forested vs. deforested area). Land changes in such binary cases are simply calculated by applying a cutoff to the suitability surface assigning the land use to the highest part of the suitability surface. The cutoff value can be determined such that the regional-level quantity of each land use type that needs to be allocated is matched (Pontius et al., 2001). In case of multiple land cover or land use types these may be allocated hierarchically based on their presumed competitive strengths. Often urban land uses are allocated first, after which agricultural land uses are allocated according to the suitabilities of the locations not yet occupied by urban land use (Letourneau et al., 2012; van Delden et al., 2007). (Semi)natural land uses often occupy the remaining locations.

In other models a more dynamic simulation of the competition between land uses or covers is implemented. This is done, for example, by accounting for the relative differences in suitability for different land uses and the overall demand for those land uses at the regional level or through the dynamic calculation of a shadow price for land (Verburg and Overmars, 2009).

Neighborhood Interactions

Neighborhood interactions in cellular models are based on the presumption that the possibility of transition from one use of land to another is dependent on the land use of the locations in the neighborhood. The theoretical underpinning for neighborhood effects was provided by Fujita et al. (1999) and Krugman (1991, 1999). Arthur (1994) used this concept to explain path dependence in the development of cities. In agricultural land use models a rationale for neighborhood interactions is provided by the process of imitation of crop choice and agricultural management between neighboring farmers or within their social network. Empirical evidence, however, has shown that such relations are not always observed as clearly as theory would suggest (Schmit and Rounsevell, 2006).

The best-known implementation of neighborhood interactions in land change models is in the form of cellular automata (CA). Made famous by Gardner (1970), John Conway's game of life is the best-known example of a cellular automaton to date. Hägerstrand (1967) and Tobler (1970) first introduced cellular automata in geography, but they were further developed by Couclelis (1985), Batty and Xie (1994), and White et al. (1997). The basic principle of CA is that land use change can be explained by the current state of a cell and changes in those of its neighbors. CA comprises four elements: (1) cell space, (2) cell states, (3) time steps, and (4) transition rules (White and Engelen, 2000). Transition rules specify what land changes will (be likely to) happen based on the nearby land cover types and can be specified based on expert opinion or derived from different types of statistical analysis to inform the specification of the neighborhood rules (Verburg et al., 2004b). However, often expert-based rules for neighborhood interaction are calibrated based on observed transitions to ensure that the algorithm reproduces the observed land cover or -use patterns.

Neighborhood interactions can also be captured in land change models by including them as part of the determinants of the local suitability, for example, by including a variable in the suitability model that represents the number of occurrences of same land use type in the neighborhood. This may be achieved by including an autoregressive term in the econometric model (Lin et al., 2010) or a neighborhood variable in the statistical and machine learning models described in the section above. Neighborhoods can vary between simple neighborhoods of surrounding cells to more complex neighborhoods based on network analysis or predefined regions.

An important consequence of including neighborhood interactions is the emergence of complex spatial patterns from relatively straightforward decision rules as result of the path dependence of the simulation. This allows representation of a number of typical characteristics of land change, such as the emergence of cities (Arthur, 1994). Given their ability to represent characteristics of complex system, CA models are sometimes described as a type of agent-based model. The key difference is that, for cellular models, spatial entities are the basic units of simulation and the topology (or connection) between those units remains fixed, whereas agent-based models (described below) represent decision making units that have a flexible and dynamic relationship with land units. The fixed structure of the cellular models is least limiting in systems where the land characteristics are reasonable indicators of the actor characteristics (e.g., farmers on agricultural land are different from residents of urban land) and where movement of actors of different types among locations is not a significant aspect of system dynamics.

Top-down or Bottom-up Determination of Aggregate Land Change

Amounts of land use and land cover change are determined in a top-down fashion when observations or projections of the aggregate rate of change are available for the region as a whole. These land use–change estimates are used as to bound an allocation procedure to identify the locations of land use or land cover changes. Models using a top-down structure are constrained cellular automata models such as Environment Explorer (de Nijs et al., 2004; White and Engelen, 2000) and models like CLUE-s (Verburg et al., 2002) and the Land Transformation Model (Pijanowski et al., 2002).

Bottom-up procedures typically begin calculations at the level of the individual land units. Examples of such models using a bottom-up structure are pure cellular automata models that calculate transitions purely based on the state of the neighboring cells. Also the well-known SLEUTH model, in its original form, uses a bottom-up approach (Clarke and Gaydos, 1998). Both the top-down and the bottom-up approaches have comparative advantages. Whereas the top-down approach explicitly incorporates drivers at a higher aggregation level, in addition to local drivers that determine spatial allocation patterns, the bottom-up approach gives much more weight to local drivers as determinants of aggregate changes at higher levels. While some models are exclusively top down or bottom up in nature, some combine these approaches in a hybrid. Verburg and Overmars (2009), for example, present a hybrid approach in which the dynamics of urban and agricultural land are constrained in a top-down manner, by the trade and regional demand, while the dynamics between (semi)natural land use types is determined solely by the local dynamics originating from the site-specific conditions and land use history. This hybrid demonstration illustrated that the appropriate choice of a top-down or bottom-up approach depends on the dominant processes that influence the dynamics of a specific land use or land cover type.

Technical, Research, and Data Challenges

Cellular approaches have been extremely successful if measured in terms of the number of applications. A wide range of cellular models have been developed over the past two decades, mostly based on variations of the implementation of the concepts described above. A number of the earlier cellular models, for example, SLEUTH (Clarke and Gaydos, 1998), GEOMOD (Pontius et al., 2001), and CLUE-s (Verburg et al., 2002), have been very widely applied across case studies (see Box 2.2). Another indication of success has been the application of this modeling approach in decision support. These models have been used not only in local stakeholder dialogues on land use planning (Van Berkel and Verburg, 2012) and regional assessments (Claggett et al., 2004), but in national to global scale decision-support (Uthes et al., 2010; van Delden et al., 2011; Verburg et al., 2008).

The success of cellular models can be attributed to their relative simplicity in structure and application. The cellular data format matches very well the format of land cover data derived from remote sensing and allows a straightforward processing. Also, the underlying concepts of trend projection, location suitability, and neighborhood interactions are intuitive and can be parameterized by empirical analysis of time-series data or more advanced econometric and calibration methods. The structure of models become much more complex when parcels or other spatial units are used instead of rectangular pixels (Lazrak et al., 2010).

Cellular models are widely available, even included as part of some commercial GIS packages. Because of their availability and simplicity, these models are sometimes selected for these reasons and not because the underlying concept fits well with the case-study specifics. Operation of cellular models is tied to the spatial data layers on which they rely, not only land cover data but also the potential location factors that determine the likelihood of finding a particular land cover type at a specific location. Often, model applications are based on a rich set of physical factors describing terrain, soil, and climate conditions. Spatial variations in socioeconomic conditions, including land tenure, are generally identified as important considerations for land change, but they are sometimes ignored in model applications due to the limited availability of spatially explicit socioeconomic data (Verburg et al., 2011). However, they are included in a number of model applications through inclusion of, for example, census data, polygons representing parks or other public land, and zoning maps.

In spite of their many advantages, cellular models also have clear drawbacks. These are mainly related to the lack of clear theoretical link between the conversion rules and the actual agents of decision making. By defining the transition rules for spatial entities, like pixels, the validity of the conversion rules is largely restricted to the specific spatial extent and resolution for which the rules are defined or empirically estimated. Though heterogeneity of the land surface is represented through variables measuring land suitability and access, heterogeneity of the actors, for example residential homebuyers with different preferences cannot be represented directly. Furthermore, interactions in cellular models are almost exclusively represented by spatial neighborhoods, mostly ignoring interactions through social and other networks. Finally, scale dependency in spatial models (Veldkamp et al., 2001; Walsh et al., 1999) is an issue that makes it difficult to transfer model parameterizations across case studies and scales.

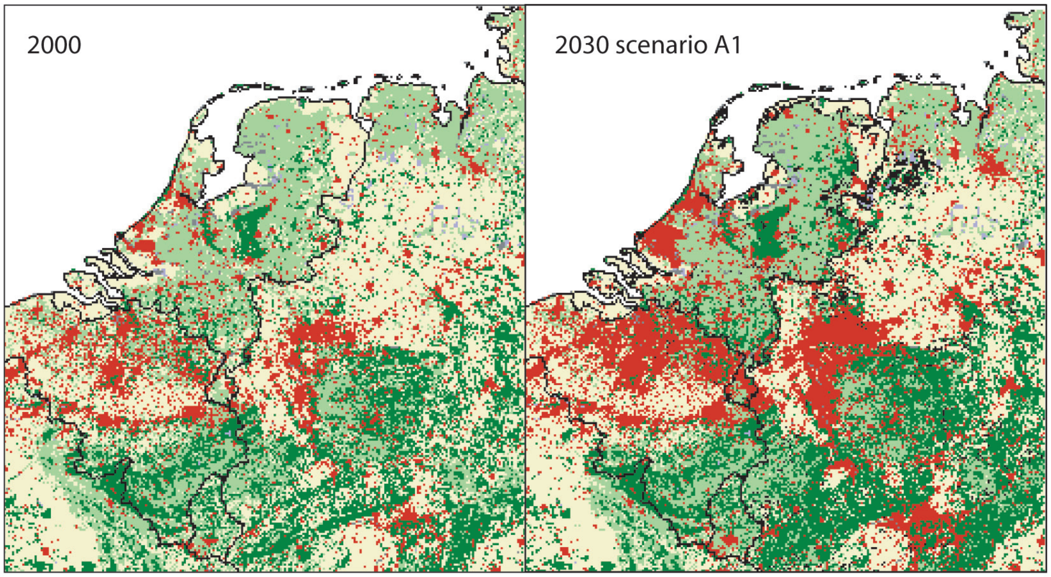
Many cellular models provide reasonable projections of land cover changes over relatively short time frames (e.g., up to 20 years). However, in cellular models run over large extents and used to inform climate change assessments, the simulations are extended to periods of up to one century and over such longer time scales, feedbacks in socioecological systems become increasingly important. Scarcity of land resources, perception of environmental impact, the functioning of the global economic system, as well as policy responses may lead to a modification of conversion rules as a result of preceding land changes and changing decision-making strategies by agents (Meyfroidt, 2013). Cellular models that include neighborhood interactions in the transition rules include feedbacks more explicitly as the neighborhood state is updated during each simulation step. However, the model rules generally use the same algorithm (with different inputs) over space and time, limiting the representation of endogenous adjustments to feedbacks, leading to greater potential for significant divergence between projections and actual outcomes over longer time frames. In principle, cellular models are capable of implementing feedbacks into the rules and model structure, but examples of their implementation are rare (Claessens et al., 2009).

BOX 2.2

Modeling Land Change Under Alternative Policy Scenarios In Europe

The CLUE (Conversion of Land Use and its Effects) model is one of the most frequently used land use models worldwide. Although the original model was published in 1996 it has been frequently updated and improved to take stock of the recent advances in land science and developments in environmental modeling. Different versions of the CLUE model, especially Dyna-CLUE and CLUE-scanner, have been frequently used in European applications to support policy discussion and ex ante evaluations (UNEP, 2007; Verburg et al., 2008). Currently an operational version of the model is used by the European Commission Joint Research Centre for routine assessments. The CLUE model is a cellular model that uses a top-down allocation of land use demands calculated by nonspatial models. Its allocation is based on suitability maps that are estimated using current-day relations between land use and location factors. Neighborhood interactions are included for urban land uses in a manner similar to cellular automata models to represent agglomeration effects.

For the European application, CLUE operates on a 1 km^2 spatial resolution and yearly time steps. This resolution makes it possible to account for specific spatial policies and location-specific driving factors. In the case of adaptation and mitigation measures, such regional specificity is important to capture the feedbacks of local conditions and governance to macroscale patterns of land change. The spatial detail is needed to make sufficiently accurate assessments of land change effects on emissions and other ecosystem services (Kienast et al., 2009). This is especially true for the determination of land change effects on emissions of carbon and other greenhouse gases, where the location of land change is of prime importance. Tailor-made and scale-specific impact assessment modules, documented in peer-reviewed literature, are available for assessment of impacts of land change on carbon, hydrology, ecosystem services, and biodiversity.



Example of a cellular model run for one scenario for the 2000-2030 period showing strong urbanization as well as agricultural abandonment for the northwest of Europe. SOURCE: Kienast et al., 2009

SECTOR-BASED AND SPATIALLY DISAGGREGATED ECONOMIC

Theoretical and Empirical Basis

Economic models of land change begin with a *structural model* of underlying microeconomic behavior (e.g., utility or profit maximization) that determines demand and supply relationships and generates aggregate outcomes of prices and land use patterns. Focused on the economic behavior of human actors, economic models tend to focus on land use, as opposed to land cover, though they can be included within integrated models that also produce land cover outputs. Fundamental to economic models is the price mechanism, which both determines individual choices and is determined by the cumulative choices of all individuals within a given market area. The concept of equilibrium is used to ensure that individual choices and aggregate outcomes are consistent with each other. Although equilibrium may be defined in various ways, the condition of market clearing, meaning that prices adjust such that markets clear (i.e., excess demand and excess supply are zero in all factor and output markets), is standard in these models. Equilibrium may be static, in which case agents are myopic and prices and land use patterns are unchanging, or dynamic, in which case agents are typically forward looking and prices and land uses are changing over time subject to a constant market-clearing condition. For example, the basic economic land use model posits a landowner's land use decision as a profit-maximizing decision in which the landowner chooses the productive use of the land that maximizes the landowner's net returns. Whereas a model with static expectations considers only net returns in the current period, a model with dynamic expectations accounts for the forward-looking expectations of landowners over future costs and returns, which influences the land use decision today. Economists typically use the word *dynamics* to mean forward-looking behavior while others use it to mean changes in state variables over time without specific regard to expectations (Irwin and Wrenn, 2013). Both types of dynamics are important in the context of land use modeling. Forward-looking behavior is a critical element of many economic land use models—for example, farmers that make current planting decisions based on anticipated future prices of agricultural commodities. Accounting for changes in land use over time is an equally important modeling goal, particularly for policy scenarios.

Structural economic models are specified based on a number of maintained assumptions (e.g., of agents' behaviors, market structure, and functional form) and the parameter values are often estimated using econometric methods. In other cases parameter values may be guided by theory, taken from previous studies reported in the literature, or a range of values may be explored to examine the sensitivity of the model to specific parameter assumptions. A fully specified structural model can be simulated to generate predictions of prices and land use outcomes under baseline and alternative conditions. The advantage of a structural approach is that, by modeling the underlying processes explicitly, it is possible to account for aggregate-level feedbacks from market interactions (e.g., a change in the price of a substitute good) or nonmarket feedbacks (e.g., congestion externalities) that influence the equilibrium. A structural modeling approach is necessary when the goal is to evaluate the impacts of a nonmarginal change, including policy changes, on land use outcomes or to generate projections of future land use changes under alternative scenarios. This is particularly important when modeling complex processes like land use, in which nonmarginal feedbacks can arise from interactions within and between the socioeconomic and biophysical systems. Because the structural models explicitly describe economic processes and interactions, their reliance on the stationarity assumption is less limiting than for the statistical, machine learning, and cellular models. Structural models may represent only one or several interdependent sectors of the economy (partial equilibrium) or may include all input and output markets of the economy (general equilibrium). Because of their added complexity, general equilibrium models are defined at more aggregate spatial units (e.g., at the scale of a county, region, or nation), whereas partial equilibrium models can be defined either at the scale that is commensurate with the individual agent or at more aggregate scales. Although structural models rely on a number of maintained assumptions related to the equilibrium, the agent behavior, and market structure, the specification of these structural characteristics improve the fidelity of these model over statistical, machine learning, and cellular approaches to the economic processes leading to land use change. Their data requirements, however, are quite different. Remotely sensed land cover data is less useful than data on the determinants of the supply (e.g., land quality distribution) and demand (e.g., economic activity) for different land uses.

In other cases, the goal of the research is *not* to explicitly model the underlying structural processes of demand and supply, but rather to identify a causal relationship between one or more explanatory variables and the dependent land use variable. In such cases, a *reduced-form econometric model* is estimated instead. A reduced-form model can be derived by expressing the outcome variable of interest (e.g., land use, land change, or land value) as a function of explanatory variables that are hypothesized to influence profits, utility, or other primitives of the structural model. Continuing the example from above, the revenues and costs associated with a parcel's land use are posited to be a function of parcel-specific variables, including the parcel's physical land characteristics and its location relative to input and output markets. Because the focus of reduced-form modeling is on causal identification and estimating effects, a central empirical challenge is to address problems of endogeneity that arise when an explanatory variable is correlated with the error term. Such endogeneity may arise, for example, from a simultaneous relationship between the dependent and explanatory variables, omitted variables, or through a systematic, but unobserved, process that determines selection among the set of land parcels or locations that are observed. Addressing such identification challenges is the principal focus of reduced-form econometric modeling. However, because neither price formation nor any other market or nonmarket feedbacks are explicitly modeled, these models cannot be used for analysis of nonmarginal changes that would cause the system to equilibrate. For this reason, use of reduced-form econometric models for projection or prediction, like the statistical models discussed above, generally relies on the assumption of temporal stationarity. Because they are derived from an underlying economic model of behavior, reduced-form econometric models are better suited for modeling land use rather than land cover outcomes. However, when land use data are not available, remotely sensed land cover data can be used as a reasonable proxy when the relationship between land use and land cover is relatively direct, for example, deforestation resulting from agricultural expansion (Nelson and Hellerstein 1997; Pfaff et al. 2007). This is no longer the case when land cover is not a direct outcome of the underlying land use decision. For example, low density exurban development is a residential land use that is comprised mostly of vegetative (non-urban) land cover. While econometric techniques may still be used for identification, the model results reveal causality related to land cover not land use and would be misleading if interpreted in terms of land use. In the absence of a clear identification strategy, reduced-form models estimated with data on land cover provide only a pattern-based correlation analysis similar to the statistical models discussed above.

Economists have used both structural and reduced-form models defined at varying spatial scales and geographic extents to model land change processes. At the most aggregate scale, sector-based models represent global input and output markets that are distinguished by just a few homogeneous regions. At the most disaggregate scale, spatial models of individual land use decisions are estimated using spatial data on land parcels with a geographic extent of a single county. In what follows, we first discuss sector-based models, which vary in their spatial scale and extent, but are aggregate structural economic models of one or more sectors of the economy. We then consider spatially disaggregate models, which use data at the field, parcel, or neighborhood levels to model individual land use or location decisions. These models may be either structural or reduced form, depending on the research question and available data, and are defined by one or more equilibrium assumptions. These models can incorporate site-specific characteristics, such as soil quality; location attributes, such as distance to the nearest town and neighborhood quality; and individual agent characteristics. Space may enter as a source of exogenous heterogeneity or as an endogenous factor that is jointly determined with spatial equilibrium prices and land use outcomes. Examples of the latter include congestion externalities, agglomeration effects, and income sorting. Here we provide only a brief overview of these various modeling approaches. More detailed reviews of sector-based models are available from André et al. (2010), Hertel et al. (2009), Palatnik and Roson (2009), van der Werf and Peterson (2009), and van Tongeren et al. (2001). For more discussion of spatially disaggregate models see Brady and Irwin (2011), Irwin et al. (2009), and the chapters by Irwin and Wrenn (2013), Klaiber and Kuminoff (2013), and Plantinga and Lewis (2013) in *The Oxford Handbook of Land Economics* (Duke and Wu, 2013).

Sector-Based Models

Sector-based models are structural models of one or more sectors of the economy that model the flows of inputs (labor, capital) and outputs (commodities) across regions or countries in which land is a fixed factor of production. Models are distinguished by the scope of the economic system that is represented: general equilibrium models represent the global economy and the interactions and feedbacks between different sectors (markets), partial equilibrium (PE) models consider detailed description of a specific sector or sectors (e.g., agriculture, forestry production, and/or fuel production system) as a closed system without linkages with the rest of the economy. PE models determine prices, production, and the proportions (or shares) of land within a geographical region (usually a country or region) used as inputs in the agricultural, forestry, and/or fuel sectors. These models assume that economic conditions in the rest of the world remain unchanged.

Computable general equilibrium (CGE) models operationalize the general equilibrium structure by using computational methods to solve for the supply, demand, and price levels that support equilibrium across interconnected markets of an open economy (Wing, 2004). CGE models are able to capture macroeconomic processes and international feedback effects through changes in relative prices of inputs and outputs. While broad in geographic and sectorial scope, CGE models have limited spatial resolution and usually partition the world into a few large homogeneous regions. Each region has a regional representative household that allocates resources domestically and production sectors that produce goods and services using consumer-owned endowments as primary inputs. Each region interacts with other regions through trade. Consumers maximize utility, while producers maximize profits in a perfectly competitive market setting, leading to endogenously determined prices and quantities of goods and factors of production (Khanna and Crago, 2012). This representation means that heterogeneity among consumers and producers within a sector, for example in terms of risk tolerance or access to capital, are not accounted for in these models.

PE and CGE models explain the amount of land allocated to different uses by demand-supply structures of the land-intensive sectors under certain exogenously defined constraints. In addition to data tables of input and output of all included commodities, the most important inputs are elasticities, which describe, for example, the sensitivity of consumer demand to price changes and of producers' output decisions to input price changes.

Examples

Examples of PE models, which consider only the agricultural sector, are the ASMGHG model (McCarl and Schneider, 2001; Schneider, 2000), IMPACT (Rosegrant et al., 2002), and the model of De Cara et al. (2005). An example of a PE model describing the forestry sector is the Global Timber Market Model (Sohngen et al., 1999). The following models include both the agricultural and forestry sectors: AgLU (Sands and Edmonds, 2005; Sands and Leimbach, 2003), FASOM (Adams et al., 2005), and GLOBIOM (Havlik et al., 2008) (see Box 2.3).

Examples of CGE models analyzing the effect of land cover and land use change include FARM (Wong and Alavalapati, 2003), the Global Trade Analysis Project (GTAP) model (Hertel et al., 2009), the Emissions Prediction and Policy Analysis (EPPA) model (Babiker et al., 2008), and the IMAGE (Alcamo et al., 1998). These models are similar in that they are global in scope and are multiregion, multisector, and multifactor models.

BOX 2.3

The Agriculture and Land Use (AgLU) Sector-Based Economic Model

The Agriculture and Land Use (AgLU) model simulates land use change globally and carbon emissions resulting from land use policies. The model was developed as an extension of the Edmonds-Reilly-Barns (ERB) model of energy consumption and carbon emissions (Edmonds et al.,1996) which utilizes oil, gas, coal, and commercial biomass global markets (Sands and Kim, 2009).

The three primary drivers of land use change are population growth, income growth, and autonomous increases in future crop yields. Currently efforts are under way to develop the Integrated Earth System Model (iESM) by merging the GCAM model with the National Center for Atmospheric Research's Community Earth System Model to advance the science of human and Earth system interactions, including studies of land use, future bioenergy systems, hydrology, climate adaptation, and mitigation. One trade-off, however, is computational intensity for the near-limitless options in human systems and decision making. Accordingly, iESM is expected to advance a new class of human-Earth systems understanding and analytic capabilities while working in tandem with other established modeling capabilities.

Technical Research and Data Challenges

PE models are able to provide initial assessment of the costs and potentials of emission reductions for a local or regional policy option. A key limitation of PE models is that demand for a land use sector is exogenously given. If there is a shock to the system, equilibrium prices change, but it does not change incomes of consumers and producers and affects demand curves endogenously. Nevertheless, the higher level of detail that comes with a lower level of regional aggregation comes as an advantage. As the scale of the policy and the region under study becomes larger, CGE models that focus on these effects may have an advantage. However, the first generation of CGE models was overly simplistic and did not capture many important characteristics of land use economics. Over the past one and a half decades, different attempts have been made to extend CGE models to allow for detailed analyses of the land use sector. Each modeling approach has its own advantages and drawbacks in terms of data requirements, computational practices, and accuracy of representation.

There can be gains from coupling the CGE model with models of other disciplines or narrower or broader scope, for example when studying linkages between climate policy and land use. A few efforts have coupled equilibrium models with detailed biophysical models. For example, the PE model IMPACT allows for the combined analysis of water and food supply and demand. Based on a loose coupling with global hydrologic models, climate change impacts on water and food can be analyzed using IMPACT (Zhu et al., 2008). IMAGE is a biophysically based global CGE model of agriculture and land use (Alcamo et al., 1998) that provides an interlinked system of atmosphere, economy, land, and ocean. IMAGE is the first model to have considered the feedback between land use change and climate change in both directions. Like IMAGE, MIT's EPPA model is a forward-looking (Babiker et al., 2008) CGE model that is part of MIT's integrated assessment model, the Integrated Global System Model, which links a set of coupled human activity and Earth system models (Sokolov et al., 2005). However, the EPPA model focuses on fossil-fuel emissions from energy production and includes agriculture as an aggregate sector only, with land as an input that is imperfectly substitutable with the energy materials composite. Another example of a coupled modeling system is KLUM-GTAP (Ronneberger et al., 2009), where the static global CGE model GTAP is coupled to the land use model KLUM (Ronneberger et al., 2005). The biophysical aspects of land are included indirectly, as area-specific yields differ for each unit of land.

Spatially Disaggregated Models

Spatially disaggregated economic models are based on the assumption of an underlying behavior of profits or utility maximization or cost minimization, all of which are continuous variables. However, land use is typically measured as a categorical variable at the individual parcel or decision-maker level, requiring a discrete choice framework to model an individual's optimal land use decision (Bockstael, 1996). Dynamic discrete choice models that account for both the evolution of the model's state variables and how agents form expectations over future values of these variables are computationally difficult, and estimation with more than a few state variables becomes intractable. For this reason, most spatially disaggregated models model land use change over time but assume static expectations (Plantinga and Lewis, 2013) (see Box 2.4).

Structural models are distinguished from reduced-form models by explicitly representing the underlying microeconomic behavioral process (e.g., profit maximization or cost minimization) and the mechanism by which these individual decisions aggregate up to market-level outcomes. Although the basic concept of equilibrium is used to solve this aggregation problem, models differ in how equilibrium is defined in the relevant input and output markets. Models may treat prices as exogenous if the market extent is large relative to the geographic extent of the study. For example, agricultural and forest commodity prices that are determined by large regional markets and global market competition are exogenous to individual farm or forest operators (e.g., Antle et al., 2001). On the other hand, if the modeling goal is to simulate policies that may induce large-scale land use shifts, then the price-feedback effects must be accounted for by specifying market-equilibrium conditions (e.g., Lubowski et al., 2006). While most models assume frictionless markets, equilibrium conditions may also reflect market frictions that would constrain the equilibrium, such as information costs, credit constraints, or moving costs (e.g., Bayer et al., 2009). If space is important, then prices will depend not only to the quantity of land in alternative uses but also on its spatial distribution. In turn, the spatial distribution of land use depends on price and its spatial variation. Equilibrium is determined by appealing to the concept of spatial equilibrium. In a model with homogeneous agents, such as the urban bid-rent model, spatial equilibrium is characterized by equal utility or profits across space since any advantage or disadvantage of a location is capitalized into its price. On the other hand, models that account for heterogeneity in preferences or income, such as the equilibrium-locational models, characterize spatial equilibrium as a Nash equilibrium in which each individual makes an optimal decision given the location or land use decisions of all other agents (Kuminoff et al., 2010). In each case, price is the equilibrating mechanism that determines the quantity and pattern of land use and land change.

Because data on revenues and costs associated with spatially disaggregated land use choices are often not available, spatially disaggregate models are often reduced form. In many cases, the model may not be fully reduced to only exogenous variables; that is, the model may include one or more endogenous explanatory variables that are determined by the same equilibrium process as the dependent variable. For example, in the case of open-space spillovers that influence the amenity value of a location, the spatial distribution of open space is endogenous to the land market and thus the spatial pattern of residential and open space are jointly determined. In a reduced-form model, in which these structural relationships are not explicitly represented, problems of endogeneity, for example, that arise from simultaneity or unobserved correlation, violate the statistical assumptions of the model. A variety of econometric methods have been developed to address these identification problems. If properly dealt with, the estimated reduced-form model yields consistent and unbiased estimates of the net effects of the explanatory variables on the modeled land use outcome. Because of their focus on causal identification, reduced-form models are often preferred when the research goal is to test one or more specific hypotheses by identifying key parameters. For example, this is the case with reduced-form models used in quasiexperimental designs in which the goal is often to evaluate the effect of a specific policy or policy change on land use outcomes (Towe and Lynch, 2013). Reduced-form models can also be used to simulate land use change in response to a change in a policy or other variable of the model. However, because these models are limited by the assumption of a constant equilibrium, they can only be used to simulate the effect of marginal changes on land change outcomes.

In order to predict the effects of a policy or other change on two-dimensional land use patterns using a spatial disaggregated economic model, some kind of a spatial simulation approach needs to be used in addition to the statistical estimation. A challenge arises in applying the results of discrete-choice models, which are probabilistic in nature, to spatial simulation models. Although some researchers form deterministic rules from these probabilistic transition estimates, this ignores the stochastic nature of the model results. An alternative is to generate a large number of different landscapes conforming to the underlying probabilistic rules (Plantinga and Lewis, 2013). The challenge is then to summarize this information in a way that conveys the distribution of potential landscape pattern outcomes and is useful for policy evaluation. Any simulation of alternative policy scenarios or future conditions based on an econometric model necessarily relies on a stationarity assumption, that the conditions under which the simulations are made are identical to those under which model was fit. The less structural detail in the model, i.e., the less the processes are endogenous, the stronger is the stationarity assumption.

Examples

The early spatially disaggregated models were reduced-form binary or multinomial discrete-choice models of discrete land use or land cover categories (e.g., Bockstael, 1996; Chomitz and Gray, 1995; Nelson and Hellerstein, 1997). These were very similar in form to the statistical approaches described above. Subsequent innovations in modeling came with the application of duration models to account for time (and nonstationarity) and time-varying variables in the land conversion process (Irwin and Bockstael, 2002; Newburn and Berck, 2011; Towe et al., 2008) and with price data that provide a means to impute net returns at an individual level (Antle et al., 2001; Lubowski et al., 2006; Wu et al., 2004). Most recently researchers have developed econometric models that incorporate both the discrete and the continuous change aspects of land use (Lewis, 2010; Lewis et al., 2009; Wrenn and Irwin, 2012) (see Box 2.4). This is an important innovation given that both outcomes—the discrete land use change and the intensity with which the land is used—have important impacts on many issues directly related to land use and its spatial configuration including ecosystem fragmentation, loss of farmland, and urban decentralization.

Landscape simulation models differ in their research goals. In some cases, the question centers on local spatial effects and how they influence the spatial structure of markets or land use. For example, Irwin and Bockstael (2002, 2004) used estimates from reduced-form duration models to simulate the influence of local spatial interactions from neighboring developments on residential development patterns. Wu and Plantinga (2003) simulated a spatial equilibrium model based on the urban bid-rent model to examine the influence of public open space on the spatial structure of urban land rents and land use. Caruso et al. (2007) used a similar model to consider the influence of endogenous green amenities and congestion effects on the resulting urban land use pattern. Newburn and Berck (2011) developed a spatial simulation model based on the urban growth model of Capozza and Helsley (1989) to examine the influence of preference heterogeneity and differences in suburban versus exurban development costs on leapfrog development patterns.

In other cases, parcel-level econometric models have been usefully integrated with ecosystem models to examine the influence of land management policies on private landowners' land use decisions that in turn affect climate change, species conservation, water quality, or other ecosystem services. For example, Nelson et al. (2008) used National Resources Inventory plot-level data for the United States over several time periods to estimate an econometric model of a landowner's decision to allocate land to one of six uses (crops, pasture, forest, urban, range, and land enrolled in the Conservation Reserve Program). Decisions are posited to be a function of their current land use, land quality of the plot, specific landowner characteristics, and economic net returns for each land use, which are predicted at the plot level by interacting an estimate of average county-level net returns with a plot-level measure of land quality. The empirical model yields transition probabilities expressed as functions of net returns and the starting land use, which allows for the simulation of incentive-based policies by modifying net returns and using the model estimates to predict the effect on landowners' land use choices. The estimates are used to generate predicted transition probabilities for land parcels located in a western U.S. region under several different conservation payment policies. Uncertainty is accounted for by running many simulations for each policy scenario and examining the distribution of land use patterns for each scenario. Predicted land use patterns are then used as inputs into models that predict the provision of carbon sequestration and biodiversity conservation. The results show that there are trade-offs between these two ecosystem services and that policies aimed at increasing the provision of carbon sequestration do not necessarily increase species conservation.

A recent innovation in structural modeling is the application of equilibrium-locational-choice models to simulate the effects of various land use policies on housing markets and land use allocations at a neighborhood scale. Using the observed outcomes of the household sorting process and house prices across neighborhoods, it is possible to estimate structural econometric models of household location that are consistent with a spatial equilibrium. Because the model estimates reflect the underlying preference structure and how households respond to market feedbacks (e.g., a price change) and nonmarket feedbacks (e.g., open-space patterns), the model can be used to predict household location choices under future scenarios in which nonmarginal changes may cause households to resort. Walsh (2007), for example, examines how an open-space policy affects household re-sorting by changing the spatial equilibrium distribution of private and public open space across neighborhoods within a metropolitan region. He finds the surprising result that a policy to provide additional public open space can result in less overall open space as demand for these locations increases and households substitute away from private open space.

Technical Research and Data Challenges

The primary advantages of structural models of land change are twofold. First, they account for the fundamental role of prices (e.g., costs and revenues) in explaining individual land use decisions in ways that most machine learning and cellular models do not. This permits simulations of incentive-based economic policies such as payments for ecosystem services. Recent econometric models of land change have incorporated spatially disaggregated predictions of net revenues and in so doing accomplish this important goal (e.g., Lewis et al., 2011; Lubowski et al., 2006; Nelson et al., 2008). Second, models in which price is endogenous are able to capture the feedback effects of predicted land use changes on prices and thus can be used to predict the outcomes of policies that induce nonmarginal changes and cause the system to reequilibrate. Equilibrium locational-choice models provide the best example of this approach to date (e.g., Klaiber and Phaneuf, 2010; Walsh, 2007). Combining these two approaches by developing an econometric structural model of land use at the parcel level, in which the parameters of the market equilibrium are jointly estimated, is a much more difficult task and one that has not been achieved. The model by Lubowski et al. (2006) provides an alternative approach that combines econometric-based predictions of policy-induced land use changes with a policy simulation model that uses demand elasticities from previous studies to account for the subsequent changes in the prices of agricultural and forest commodities. This analysis is carried out at a national level. Accounting for market feedbacks in a spatially disaggregated land use simulation model may not be necessary for some output markets (e.g., if commodity markets are global), but assumptions regarding spatial equilibrium in more localized markets, including land and housing markets, are necessary to capture spatially disaggregated market and nonmarket feedbacks. Despite the modeling challenges, developing a spatially disaggregated LCM that accounts for such feedbacks is critical for developing spatially disaggregated, dynamic land change models and coupling land change and ecosystem models over longer periods of time.

Although structural models are necessary for nonmarginal land change prediction and policy scenarios, they also face a number of challenges. All structural models require maintained assumptions about agent behavior, market structure, and functional form. In addition, econometric structural models require a number of identifying assumptions about the error processes. Spatial simulation models, on the other hand, require assumptions about parameter values. Many of these assumptions are difficult to test empirically and therefore additional data and analysis are needed to better justify these assumptions. In some cases, structural models are also limited in the spatial dimension. Equilibrium locational-choice models, for example, are limited to a neighborhood scale of analysis. In most cases this neighborhood scale may be sufficient, but smaller-scale analysis of feedbacks and land use change may be necessary for certain research questions, for example, questions related to land fragmentation and the impact of land use change on ecosystems. Other challenges include incorporation of dynamics, both in terms of accounting for agents' expectations over the future evolution of equilibrium prices, as well as modeling the evolution of prices and land uses over time. So-called dynamic equilibrium models that represent changes in equilibrium prices, quantities, and other economic variables over time are well known in economics but are difficult to implement in a spatially explicit setting. Some progress has been made in urban economics (Desmet and Rosi-Hansberg, 2010) and resource economics (Brock and Xepapadeas, 2010; Smith et al., 2009). More work is needed to develop spatial dynamic models of land change and to specify these models empirically to make them useful for policy simulations. Finally, structural models are limited by their data requirements, given that data on revenues and costs are often difficult to obtain and that it takes a long time to develop them. Satellites are unlikely to provide much of the required data. These models require a minimum of several years to gather data, implement the model, and generate policy simulations.

Like structural models, reduced-form models have a number of strengths and limitations. The primary strength of reduced-form models is their focus on causal identification. By making explicit assumptions regarding the data generating process, the variables that are observed and unobserved, and the structure of the error process, these models go beyond simple correlation analysis, as generally employed in the statistical modeling approach described above, to identification of causal effects. This is essential to testing hypotheses and developing predictive models that can be used for policy. In addition, while assumptions are still necessary for identification and interpretation of the results, these models typically impose fewer assumptions on the data than do structural models. Finally, provided data are available, these models can be implemented in a reasonable time frame and, because the parameters reflect the causal relationships between the observed variables and equilibrium outcomes that are based on underlying microeconomic behavior, they can be usefully applied to policy scenarios.

A primary limitation of reduced-form models is their lack of a structural representation of the underlying demand and supply processes that generate the observed land use outcomes. Any application of reduced-form estimates to a simulation model implicitly assumes that the underlying equilibrium relationships, including prices, remain unchanged (i.e., are stationary). This is a reasonable assumption for marginal changes in the system, but not for scenarios of nonmarginal changes, such as the introduction of a new policy or a change in an existing policy that would induce large-scale shifts in land use allocations or prices. For this same reason, their usefulness for simulating landscape changes over longer periods of time is also limited.

BOX 2.4

Spatially Disaggregated Economic Model

Lewis et al. (2011) developed a spatially disaggregated integrated assessment model to examine the impacts of incentive-based policies on land change and biodiversity conservation. Similar to Nelson et al. (2008), the land change model starts with an econometric model of land use decision making that uses a random sample of plot-level, repeat observations from the National Resources Inventory taken at multiple points in time (1982, 1987, 1992, 1997). The authors take advantage of the panel structure of their data by estimating a random-parameters logit model that controls for unobserved spatial heterogeneity and temporal correlations, which is important for obtaining consistent and unbiased estimates of the land change model parameters. Predicted net returns for each plot are generated using county-level average net revenue estimates from Lubowski et al. (2006) and plot-level data on land quality and other characteristics. The inclusion of economic returns in the model is significant because it provides the mechanism for simulating landscape outcomes under alternative policies on payment for ecosystem services. Using predicted net revenues for each land use for each parcel, the authors calculate the landowner's minimum willingness-to-accept bid, which is the necessary payment that is needed to compensate the landowner for taking land out of production and putting it into conservation.

Because biodiversity is dependent on spatially disaggregated patterns of land use, a random sample of plot-level data is insufficient for predicting the policy impacts on biodiversity outcomes. The authors solve this problem by applying the parameter estimates from the plot-level econometric model to a complete set of cropland and pasture parcels that are contained within the 2.93 million hectares of their study region. Willingness-to-accept bids and transition probabilities for each parcel starting in cropland or pasture and ending in one of four land uses (cropland, pasture, forest, or urban) are calculated. A range of conservation payment policies are considered that differ in terms of the total budget and the subset of landowners who are considered eligible. Simulations of the predicted landscape that would exist 50 years after the policy is enacted are generated 500 times for each policy. The result is a prediction of the spatial distribution of land in conservation and agricultural production for each policy.

The authors provide a normative assessment of the policies by computing a biodiversity score for each of the simulated landscapes. This integration of positive land change and ecosystem models with a normative analysis of the economic and ecological trade-offs is something that relatively few studies have attempted, but yet is critical for policy guidance (Polasky and Segerson, 2009). The authors evaluate the efficiency of the predicted outcomes under each policy by comparing the biodiversity score of each policy at each of the budget levels to the maximum biodiversity score that is theoretically possible for each budget level. They find that simple incentive-based policies that do not account for the spatial pattern of conserved lands are highly inefficient. This inefficiency arises from the benefits of conserving large spatially contiguous areas and the inability of the regulator to spatially coordinate payments to landowners since the willingness-to-accept bids are private information and therefore the regulator cannot anticipate ex ante the resulting spatial landscape of conservation under a given policy and budget. The authors conclude that an auction mechanism to elicit landowners' willingness-to-accept bids and some means to provide incentives for enrollment of spatially contiguous lands are likely necessary to achieve real efficiency gains.

AGENT-BASED

Agent-based models (ABMs) represent, in computer code, systems that are composed of multiple heterogeneous and interacting actors (i.e., agents; Brown, 2006). These systems are often referred to as “multi-agent systems” (Wooldridge, 2002) and describe intelligent agents, their interactions, and their natural environment. The term “individual-based models” is commonly used in the ecology literature to describe models of this sort in applications to ecological systems (DeAngelis and Gross, 1992). In the context of land change, agents can include land owners, households, farmers, development firms, collectives, migrants, management agencies, or policy-making bodies, that is, any actor that makes decisions or takes actions that affect land use or land-cover patterns and processes (Parker et al., 2003). Agents are discrete entities that are characterized by both their attributes and their behaviors. The attributes of agents can be continuous measures, like the amount of available capital, or discrete categories, like “has children” or “belongs to a cooperative.” Agents can interact with each other and with the environment in which they live to collect information or carry out actions that modify their context. Though not all agent-based models are spatially explicit, those used in land change research nearly always are, meaning that the agents and/or their actions are referenced to particular locations on the Earth’s surface. Because ABMs instantiate a conceptual model that specifies the agents, the attributes, actions, and interactions, they are structural models that represent the processes of land change explicitly.

Theoretical and Empirical Basis

ABMs belong to a category of models known as discrete-event simulations (Zeigler et al., 2000), which run with some set of starting conditions over some period of time, allowing the programmed agents to carry out their actions until some specified stopping criterion is satisfied, usually indicated by either a certain amount of time or a specified system state. By simulating the individual actions of many diverse actors, and measuring the resulting system behavior and outcomes over time (e.g., the changes in patterns of land cover), ABMs can be useful tools for studying the effects of land change processes that operate at multiple scales and organizational levels. Measured at some time in the future, these system outcomes can also be used to evaluate projections of land use, land cover, or other state variables. Because agents can adapt their behavior to changing conditions, the stationarity assumption can be somewhat relaxed in ABMs. To the degree that ABMs rely on input data from some period of time to establish parameter values or fix decision processes that do not adapt in other ways (e.g., through learning mechanisms) to changing contexts, projections into the future will necessarily require the assumption of stationarity parameters and decision processes. So, while ABMs can be constructed in ways that relax the assumption of constancy in relationships (i.e., stationarity), they are not always constructed in that way. Because of this ability to relax assumptions, however, ABMs are well suited to representing complexity in land systems.

ABMs have been used for a wide range of applications, from explaining spatial patterns of land use or settlement and testing social science concepts, often using exploratory-theoretical models, to policy analysis and planning, more often using empirical-predictive models (Matthews et al., 2007). Models and applications toward the exploratory-theoretical end of this continuum tend to resemble a range of complex systems models that are often mathematical or analytical in nature (LUCC, 2002), including some cellular automata models. Applications of ABMs that aim to test concepts or explain patterns are often compared with analytical models of the same system to demonstrate how the ABM (e.g., because of heterogeneity and interaction) produces results that deviate from a simpler mathematical model. For example, an ABM used to evaluate the relationship between the width and location of a greenbelt and patterns of urban sprawl was able to recreate results from a simple one-dimensional analytical model, but it also demonstrated the sensitivity of results in that model to assumptions about homogeneity in agent preferences and in the landscape, and to feedbacks between agent preferences their location relative to the greenbelt (Brown et al., 2004).

Models and applications toward the empirical-predictive end of the model-application continuum require increasing support from empirical observations to orient the models toward more realistic representations of real systems. Land change applications of ABMs have incorporated a variety of empirical data types into the description of agents, thereby providing some empirical support for the types, characteristics, beliefs, and knowledge of agents (Robinson et al., 2007; Smajgl et al., 2011). These data inputs have been derived from social surveys (Berger and Schreinemachers, 2006), participant observation and ethnographic methods (Huigen et al., 2006), field and laboratory experiments (Castillo and Saysel, 2005; Evans et al., 2006), a "companion modeling" approach that uses participatory methods to engage agents in the construction of their model (LePage et al., 2012), and Geographic Information System (GIS)-based spatial data (Irwin and Bockstael, 2002). Additionally, a variety of approaches has been employed to evaluate the outcomes of models, often through evaluation of predictive accuracy (e.g., Brown et al., 2005). An approach to evaluating model outcomes, referred to by Grimm et al. (2005) as *pattern-oriented modeling*, identifies primary and secondary patterns that a model can produce and that can be compared with observed patterns in data. When outcomes of interest involve spatial patterns on land, a common method is to use satellite or aerial imagery to construct maps of land categories at multiple points in time and to compare maps generated by the models to these observations and to employ statistical descriptions of the degree of match. ABMs can be used to model land use, land cover, or both. If land cover, the decisions that affect land cover and land management need to be represented explicitly, and the theoretical basis for modeling these land cover or management decisions is not as fully developed across different systems as is land use theory. When they represent land cover patterns, ABMs benefit from Earth observation data, but data to inform agents attributes, their social interactions and decision processes is more commonly required for these models.

Issues of multi-finality and equifinality, due to exogenous control, path dependence and multiequilibria, affect the predictability of these complex systems and, therefore, the usefulness of traditional measures of predictive accuracy of these models. The pattern-oriented modeling approach can use a wider range of patterns, or "stylized facts" (Janssen and Ostrom, 2006), to validate the model. For example, a model of rubber crop adoption in Laos (see Box 2.5) was evaluated in terms of the amount of land area planted in rubber, the rate of adoption in the study area, and the income inequality among the farmers of the region (Evans et al., 2011). In application, ABMs are then commonly used to generate alternative future scenarios that can be compared in terms of how the patterns respond to changes in model inputs, parameters, or structures, rather than making point predictions.

The most important strength of agent-based models is the ability to explicitly represent agent behavior while providing a range of options for representing that behavior (An, 2012). Many economic land use models derive from assumptions of profit or utility maximization that are assumed to fully determine actors' land use or location decisions. In addition to these behavioral assumptions, these models typically consider only limited sources of agent or spatial heterogeneity. Finally, even when uncertainty enters the model, agents are assumed to form rational expectations based on a known distribution of the stochastic process (e.g., Capozza and Helsley, 1990). Research in behavioral and decision modeling (An, 2012; NRC, 2008b) has produced a range of alternative behavioral models that incorporate cognitive processes and uncertainty to explain human decision making and that can be implemented and evaluated with agent-based models. For example, (a) land use actors can exhibit heterogeneity in their attributes, preferences, or decision-making strategies.

Robinson, 2006); (b) the amount of information available to agents and effort agents use to search for and/or evaluate alternatives can limit, or bound, their level of rationality (Manson, 2006; Simon, 1997); (c) alternatives to utility maximization include, for example, using satisficing behavior, in which agents select alternatives that are "good enough" using heuristics to determine agent choices (Gotts et al., 2003); (d) agents can learn from and adapt to their environment and, therefore, evolve their approaches to accessing information, their preferences, and their decision strategies (Magliocca et al., 2011); (e) the influence of updated social networks, which can have variable and dynamic structures, can have powerful influences on decisions by affecting availability of information and resources (Entwisle et al., 2008); and (f) uncertainty and variability in environmental conditions, information availability, or decision outcomes can affect agent behaviors (Zellner, 2008).

BOX 2.5

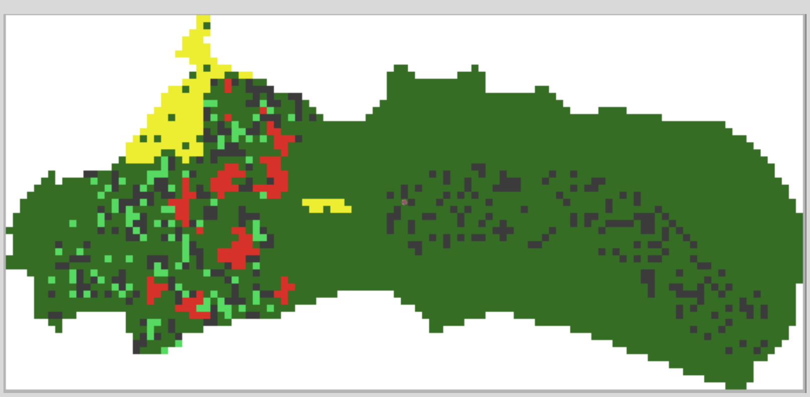
Agent-Based Model of Rubber Adoption in a Laos Village

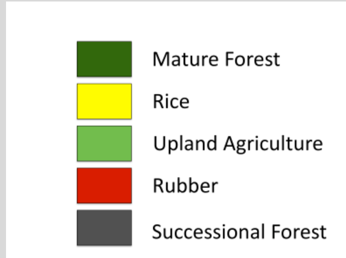
Montane mainland Southeast Asia is a region of great biological and cultural diversity that has seen the conversion from traditional agricultural systems to more permanent cash crops driven by regional and global markets (Fox and Vogler, 2005). This conversion has primarily been from traditional agriculture to commercial rubber production and is driven by decisions at the household level in which small land holders to convert their land.

An agent-based model was used to investigate the transition from shifting cultivation to rubber production for a study area in northern Laos PDR to assess changes in household-level inequalities with the transition from shifting cultivation to rubber adoption (Evans et al., 2011). Parameters on household-level land use preference and risk tolerance in the model were fit so that the model reproduced historical land cover patterns (see map below) and household allocations of land to rubber versus upland crops developed from field interviews. The interviews indicated that households with different assets, experience, and risk tolerance had different approaches to this new opportunity resulting in heterogeneity of land use and income.

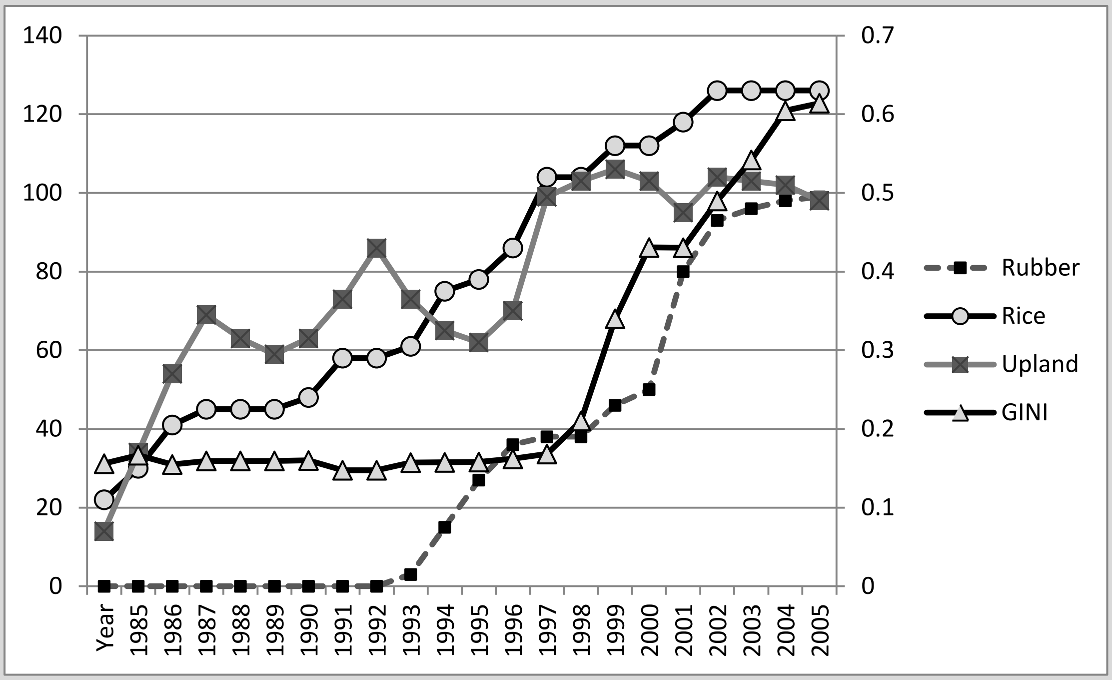
The model calculated a dramatic change in income inequality through the 1984-2006 simulation period (see graph below). The model demonstrates several pulses of rubber adoption and that labor is not the constraining factor as some households continue to allocate a majority of their labor to upland crop production through the model simulation.

The model produces a pattern of early adopters and late adopters that fits well with theories regarding the diffusion of innovation. This approach provides insight on the impact of agricultural innovation on inequality.





Simulated land cover 2006 (Evans et al., 2011).



Simulated land cover areas (ha) and Gini coefficient (Evans et al., 2011).

By explicitly representing heterogeneous agents and the interactions among agents and between agents and their environment, ABMs are particularly useful for modeling the formation of outcome patterns, like bilateral prices formed through a series of transactions (e.g., Filatova et al., 2009), or patterns on a landscape (e.g., Jepsen et al., 2006), which result from a system that lacks centralized control. This is particularly important where the combination of interactions at the agent level and heterogeneity among agents produces nonlinear dynamics at the aggregate level and renders aggregate or representative-agent models inadequate. For example, a model that included a skewed distribution of risk preferences, as observed in survey data, produced patterns of land rights and development that better matched the observed situation near the Dutch coast than did a model that included agents with homogenous risk preferences (Filatova et al., 2011). Decentralized systems of heterogeneous and interacting agents can exhibit path dependence, such that different equilibria are reached depending on the starting point or the order in which actions are taken (Brown et al., 2005). For example, the size distribution of farms and their productivity in a region after a period of time can be dependent on the average farm size for the first period, with implications for approaches to regional structural change.

Because behavior is represented explicitly in ABMs as a decision-making process carried out by heterogeneous agents, the models align with conceptual models of land use systems involving the interactions of multiple types of actors. Because the actions and outcomes of individual agents can be tracked within a model, it is easier to communicate the structure and function of an ABM to stakeholders than a model that represents agent-level decisions and actions in a stylized or aggregate manner through mathematical or statistical functions. This alignment has facilitated a number of applications in which ABMs are used alongside role-playing games to facilitate participatory modeling and learning about resource management problems (Barrateau et al., 2001; d'Aquino et al., 2003; Dumrongrojwatthana et al., 2011). This approach has been referred to as "companion modeling" and has been most vigorously pursued by the developers of Cormas, based in France (LePage et al., 2012). As models become more complicated, with more detail that provides for greater fidelity with real-world systems, however, this communication advantage can be lost. An intuitive understanding of even a moderately complex model can be challenging, and often requires both an understanding of the underlying code and experience with sensitivity analysis through running the model interactively by changing parameter values.

Agent-based models are being coupled with models' natural processes. to understand dynamics in coupled natural and human systems. Though this has often involved mainly loose coupling to date, that is, passing output from one model to another, ABMs of land change are increasingly being tightly coupled with environmental models of various sorts. For example, by coupling an ABM that represented demographic and economic processes of households with models of forest growth and panda habitat, An et al. (2005) were able to demonstrate the effects of energy and internal-migration policy in China on panda habitat. Coupling models in this way offers promise for exploring dynamics of coupled natural and human systems, and for understanding the role of feedbacks in land system dynamics (Liu et al., 2007).

Technical, Research, and Data Challenges

Many of the challenges related to the use of ABMs stem from their resource-intensive nature relative to model design, implementation, parameterization, calibration, and execution. Because models are usually designed with specific questions in mind and can require significant investments in data about both agent-level characteristics and aggregate outcomes to apply in specific settings, a given model may not be generalizable across other situations or scientific and research applications. For these reasons, problems that are simpler (i.e., can be explained with simpler analytical models) or focused on prediction rather than structural explanations may not need ABMs and the effort involved. Also, because the range of potential systems that can be represented in ABMs is quite large, it is quite reasonable to expect that the theory and data needed to build a model may not be fully developed in any given instance. In these cases, development and analysis of an ABM might usefully contribute to the development of theory or the identification of data collection requirements.

The computational and empirical resources required to implement and apply ABMs have limited their application in land change science to local-scale questions and applications. Efforts have been made recently to develop probabilistic (Valbuena et al., 2010), aggregation (Rounsevell et al., 2012), and metasimulation (Zou et al., 2012) schemes for generating and applying the insights of ABMs to regional and even global scales. Challenges remain in broadly applying and comparing these schemes and evaluating them through formal calibration and validation activities. Furthermore, approaches of this sort can be used to provide structures by which insights from multiple case studies conducted at local scales can be aggregated for understanding and integration at regional and global scales and to identify how to make compromises between spatial extent and agent complexity (e.g., larger spatial extents may require fewer or simpler agents due to computational constraints).

The following additional challenges were identified by participants in our workshop:

- Economic models of behavior commonly incorporate processes of expectations formation and forward-looking behavior. These processes are not often well developed in many agent-based models, and best practices for doing so need to be developed.
- More modeling work is needed to bridge the gap between spatial economic models and ABMs, building on the strengths of each approach. Because agent-based models do not enforce an equilibrium or spatial equilibrium condition, models that represent market processes employ ad hoc assumptions to specify the bidding and market interaction processes. In the absence of one or more closing conditions that establish an equilibrium, there is no way of ensuring that these individual behaviors will generate land prices consistent with a market equilibrium (Chen et al., 2011). In addition, because of data requirements, these assumptions of bidding behavior and market interactions are difficult to test. Comparisons are needed between spatial equilibrium models that incorporate agent heterogeneity, but rely on a static spatial equilibrium assumption to derive market prices, and agent-based models that incorporate heterogeneity, alternative types of behaviors, and dynamics over time, but that use ad hoc approaches to derive market prices.
- There is need to develop methods to standardize and improve efficiency of parameterizing agent decision models. For example, links between statistical and agent-based modeling could be better developed, such that methods for calibrating preference and decision functions for use in ABMs can be developed using econometric, experimental, and participatory approaches.
- Increasing call for use of ABMs in predictive settings will require better methods for assimilating data and updating models on the fly. For example, operational models will need to be able to be updated when an exogenous shock occurs.
- Agent-based modeling efforts benefit from the availability of a wide range of data types.

These include survey data that are spatially referenced to parameterize decision functions; data on land management, use, value, and ownership to complement land cover data; and longitudinal versions of all of these data types. Efforts to collect, make accessible, and integrate these data will enhance these modeling activities.

- Additional work is needed on methods to integrate data across disparate sources. For instance, data developed using different functional unit definitions, spatial extents, different levels of aggregation, and by different agencies might need to be integrated within a single ABM and could be harmonized through a variety of interpolation, down-scaling, or up-scaling approaches. Currently researchers often recreate data because they are not able to access and/or integrate existing data.
- The *structural validity* of the rules and algorithms used to represent agent actions and their interactions in these models has been challenging to demonstrate. For ABMs, the validation of agent dynamics is often more important than the validation of the model outcomes that are the most common validation targets for LCMs.
- Because agent-based models can frequently generate multiple outputs, due to stochasticity of parameters or inputs, it is important to evaluate the diversity of models outcomes that can result from them. This is especially important when combined with evaluation of multiple scenarios, defined by alterations in model settings to reflect alternative possible futures or policy interventions. Stronger norms for full exploration of the space of model outcomes is needed in land change modeling. This goal might benefit from cross-fertilization of methods from other modeling communities to learn how to synthesize many runs (Monte Carlo–type approaches).
- Development of new, dynamic, and multidimensional methods of analysis and visualization is needed to help better understand relationships between model parameters and model outputs. These methods can further be used to convey to stakeholders what a model is actually doing and can be used to display behaviors of individual model components (like agents or locations).
- There is a general need for standards and norms for documenting and sharing agent-based models. A National Science Foundation–funded effort to coordinate research, dissemination, and documentation of agent-based models has produced a web-based portal for model sharing (i.e., openabm.org), and the ongoing research on the standards of evidence and communication regarding use of models in science is crucial to further uptake and credibility of these modeling activities.

HYBRID APPROACHES

Many LCMs are not easily classified into one of the categories discussed in the preceding sections. Here we address the fact the conceptual and methodological approaches described above are quite often used in combination to represent various aspects of land change patterns and processes. For example, machine learning and statistical approaches are often used to develop suitability maps that then serve as one of the inputs to a cellular model that incorporates land suitability with neighborhood effects to project future land use (Almeida et al. 2008; Li and Yeh 2002) or land cover (Hilbert and Ostendorf 2001) patterns. Similarly, sector-based economic models have been integrated with spatial allocation models to downscale land areas determined in large-scale general equilibrium and integrated assessment models for large world regions to individual pixels. The Global Land Model (Hurtt *et al.*, 2011;Hurtt *et al.*, 2006) uses a relatively simple expert-based ranking of relative suitabilities in combination with an assumed hierarchical ordering of allocation. Other allocation mechanisms are possible, building on the statistical, machine learning, and cellular approaches described above. As a final example of hybrid models, coupled representations of land use and land cover dynamics, as a means of representing the dynamics of both the natural and the human processes involved in land change, have been developed by combining the statistical, cellular and agent-based approaches described above. For example, An et al. (2005) were able to successfully represent interactions between human demography and fuel use, and availability and quality of panda habitat by representing dynamics in the human communities with agents and the forest dynamics and habitat characteristics with cellular models that incorporated algorithms for forest growth and habitat suitability, some of which had been developed using statistical models for determination of suitabilities.

Theoretical and Empirical Basis

Land change is the result of multiple human-environment interactions operating across different scales ranging from global trade of food and energy to local management of land resources at the farm and landscape level. It is represented in data ranging from satellite observations of land cover to surveys of human attitudes, perceptions, and behaviors, with many other types of data in between. So far, researchers have not succeeded in defining an all-compassing theory of land change, and the feasibility of formulating such theory is not evident. Additionally, we have not yet reached the point where we have all the data we need to characterize the various land use and land cover changes that are occurring in various systems throughout the world. Therefore, it is reasonable to expect that some hybridization of the above approaches, accounting for the heterogeneous theories and data environments confronting models that incorporate land use and land cover change dynamics, is necessary to serve contemporary scientific and management purposes.

Theories from multiple disciplines, such as economics, geography, demography, ecology, and anthropology, contribute to the explanation of land change. Often, these theories are related to specific land conversion processes or sectors, for example, ecological succession (Cushman et al. 2010), Boserupian theory concerning the effects of population on land use sustainability (Boserup, 1965; Turner and Fischer-Kowalski, 2010), the induced-intensification thesis (Turner and Ali, 1996), neo-Thünen theory about moving frontiers and urban markets (Walker, 2004;Walker and Solecki, 2004), and the theories of Fujita and Krugman about urban development (Fujita et al., 1999a,b), as notable examples. Most theories cannot adequately explain the complexity of land use decision making, nor address the processes driving both land use and land cover change.

It is well understood that decision making processes about land change, as well as many of the ecological and disturbance processes affecting land cover change, are context dependent and one or multiple theories may provide a proper representation for a specific case study or land change process. Therefore, the choice of theory and model concept may depend on the specific scale of analysis, the processes studied, the availability of data, and the case-study characteristics. As an example, in a mature land market, models based on economic theory may best be able to capture the dominant processes. In a deforestation frontier the land market may not be functioning at all and models driven by geographic or institutional factors may be more useful.

At the same time, land change may be influenced by several types of processes synchronously that require different modeling concepts: for example, although land decision makers may be oriented towards optimizing benefits of land use, these benefits are often influenced by land change in the neighborhood, creating scaling effects. Because land change modeling often involves representation of cross-scale interactions, interactions among different land types or sectors, and determination of both the amount and spatial pattern of land cover types, there are multiple procedural opportunities for including different modeling approaches. While some opportunities for hybridization (e.g., for representing different land sectors) are driven by differences in the theoretical basis for such models, others (e.g., for crossing scales) are driven by the relative efficiency of different algorithmic approaches to linking across scales and processes, and still others, e.g., linking models of land use and land cover, are driven by multiple concerns that also include data availability. Hybrid modeling approaches therefore can combine different underlying conceptual frameworks, theories, and empirical observations into a system representation and allow the modeler to choose appropriate procedure for modeling depending on the practical needs of modeling across the range of representation in land systems.

Hybrid approaches can involve:

1. a combination of approaches to more fully represent decision making, for example, agent-based decision making that includes a cellular neighborhood model to account for neighborhood interactions in the decision making, or a machine learning model to represent human cognition (e.g., Manson 2005);
2. the use of different approaches for different scales to capture the dominant processes at the scale addressed, for example, economic models for aggregate land shares that constrain cellular spatial-allocation models (e.g., Sohl et al., 2012);

3. the use of different modeling concepts for different land change types considered, for example, using a cellular automata (neighborhood-based) model for urban land use with an econometric approach for other land cover types (Verburg and Overmars, 2009); or
4. the use of one approach to parameterize a model using a different approach, for example, machine learning to parameterize a cellular model (Pijanowski et al., 2005; Sangermano et al., 2010).
5. the conceptual integration of modeling frameworks, for example, the development of a common language to refer to automata with fixed (i.e., cellular) versus flexible (i.e., agent-based) topologies (Torrens and Benenson, 2005).

Strengths and Weaknesses

Hybrid modeling approaches take advantage of the strengths of the individual approaches and reduce some of their inherent limitations. The lack of overarching theory or systems description in some cases, and data or both in others, makes it necessary to carefully match existing theories and modeling concepts to the conditions and empirical contexts under which they are valid. Hybrid approaches allow such flexibility. At the same time, hybridization of modeling concepts allows the development of novel approaches can better represent the complexity of reality.

Hybridization also involves risks. Often the combination of multiple concepts leads to an increased complexity reducing the ease of interpretation of simulated changes and hampering causal tracing of emergent land changes. For this reason, model calibration and validation across the multiple hybridized components can be challenging. Separate components of a hybrid model might be calibrated in different ways, according to the empirical demands of each approach, but there is often little theoretical guidance on how the combination of components should be parameterized. As with any modeling approach, the ways the combination of model types represents reality and to what extent the model is able to answer the questions of the stakeholders of the modeling effort will determine its success.

A COMPARISON OF LAND CHANGE MODELING APPROACHES

Ultimately, the aims of land change modeling are to advance the science of land change, to improve our understanding of interactions between land change and various environmental processes, and to provide capacity to support decision making around problems involving land change. For these purposes, the various modeling approaches reviewed here provide capabilities to explain and learn (EL) about land system dynamics, as well as to project and predict (PP) future states of land systems. The ability to evaluate the impacts of environmental and social changes on the land system, especially through the use of scenarios, and to provide input to other models is also an important use to which models have been put.

We have arranged the five main modeling approaches in our assessment roughly in order from those most focused on modeling pattern (beginning to Machine Learning and Statistical Approaches) to more structural models that focus more on the processes of land change (including Economic and Agent-Based Approaches) (Table 2.1). While an evaluation of the validity of any given model or approach for any given purpose is beyond the scope of this assessment, we were able to identify some of the implications of these broad differences for how models based on these approaches can be used. In general terms, models that have a more explicit representation of a given process, like those that represent land use decision making with structural Economic or Agent-Based approaches, are more flexible to different types of changes in context that can be evaluated through model scenarios, including for example changes in credit availability, the level of enforcement for illegal activities, or the amount of information available about alternative choices. Paradoxically, perhaps, models with a greater degree of explicitness in representing process, while useful for predicting the consequences of alternative scenarios qualitatively, often perform less well making quantitative projections or predictions about specific outcomes at specific places or times. This can result from their inclusion of processes for which parameter values are unavailable empirically or are highly uncertain, feedback processes that can create path dependent outcomes with multiple equilibria, thereby raising the level of uncertainty in predictions, or processes that produce outcomes for which semantically compatible observations are unavailable. The key example of this latter point is the challenge, especially over large extents, of obtaining spatially explicit land use information. The need for land use data, due to its relative incompatibility with satellite measurements, is a mismatch with which the LCM community consistently struggles. For these reasons, approaches that are focused on fitting observed patterns (like Statistical and Machine Learning approaches) and extrapolating them into the future can both satisfy the users for which making near-term predictions is an important goal and make efficient use of the extensive record of spatially explicit land cover and other remotely sensed observations. As we have discussed in Chapter 1, these models are not limited by data so much as they are by a lack of representation of the theory behind our understanding of land change processes. Machine Learning approaches can represent well the relationships between, for example, land cover changes that are observable in multiple Landsat images over time and a variety of biophysical, location, and other variables, and used these relationships for extrapolation to estimate where future changes might be expected to occur. As long as the structural elements of the system remain unchanged (i.e., are stationary), projections can provide useful information about near-term changes. Because of their thinner theoretical and process grounding, however, models that focus on observed patterns are limited in their ability to support evaluations of scenarios involving structural change. While no single modeling approach can serve all purposes equally well, each of the modeling approaches we describe has been adapted within a wide variety of settings, often to move them along this pattern-process continuum, and the hybrid modeling approaches that combine specific approaches provide particular flexibility in developing models that address particular challenges.

Table 2.1 Generalized characteristics of modeling approaches. Column 2 indicates the arrangement of approaches along a continuum of focus on pattern vs. process. Column 3 addresses the types of outcomes (land use, land cover, or both) for which each approach has tended to be applied. Column 4 lists key assumptions that characterize how the approach. Column 5 describes the input data requirements and Column 5 lists key recommended uses.

Modeling Approach	Pattern-Process	Land cover, Land use	Key Assumptions	Typical Data Requirements	Recommended Uses
Machine Learning and Statistical	Pattern ↑	Land cover	Strong stationarity	Land cover maps from at least two time points Some number of maps of predictor variable(s)	Make forecasts of land cover patterns under stationarity Extrapolating past patterns
Cellular		Land cover, land use	Stationarity Strong spatial control and/or interaction No market interactions	A land cover map at some point in time Some number of maps of predictor variable(s)	Forecast land cover patterns Evaluate changes in spatial controls without market feedbacks
Spatially Disaggrega ted Economic Models	↓	Land use	Utility or profit maximization Price and/or spatial equilibrium Heterogeneous agents sometimes specified	Data on land use or land cover at one or more point(s) in time Economic and biophysical variables that influence land demand and supply Any other required instrumental variables	Reduced-form models: Identify the causal effect of key variables on land change outcomes Structural models: Simulate effects of policy changes on land market outcomes, including changes in prices and land use patterns
Sector-Based	Process	Land use	Utility or profit maximization	Economic variables that	Forecast aggregate land

Economic Models			Price equilibrium Representative agents	influence aggregate demand and supply, including prices of commodities and values of trade at a regional or country scale	changes under a variety of market-based changes that can affect demand and supply
Agent-Based Models	Process	Land cover, Land use	Usually heterogeneous agents Variable interactions among agents	Data describing characteristics of agents Qualitative or quantitative data on decision processes Data on land use or land cover at some point(s) in time	Explore land change processes, often under stylized conditions Explore effects of exogenous change on a system, where it has not happened Explore future scenarios where past patterns may be poor indicators of future outcomes

The relative strengths of the approaches with respect to representing patterns and processes, then, further affect their appropriateness within policy- and decision-making contexts. The committee considered the roles that LCMs can play within the context of the cycle of policy and decision making presented in Chapter 1(adapted from Verdung, 1997), and developed an approximate mapping of modeling approaches to stages in that cycle (Figure 2.2). Within this mapping, we identify the suitability of machine learning and cellular models in the problem identification step, because of their assumptions of stationarity and lack the richer structural detail about process needed to evaluate the effects of changes in policy structure. Projections of future trends can be useful to identify situations in which significant problems may arise if action is not taken, for example in managing total maximum daily loads in an area experiencing significant urban growth. These modeling approaches can also be useful at later stages, where, for example, policies or decisions that involve changing or constraining land changes spatially

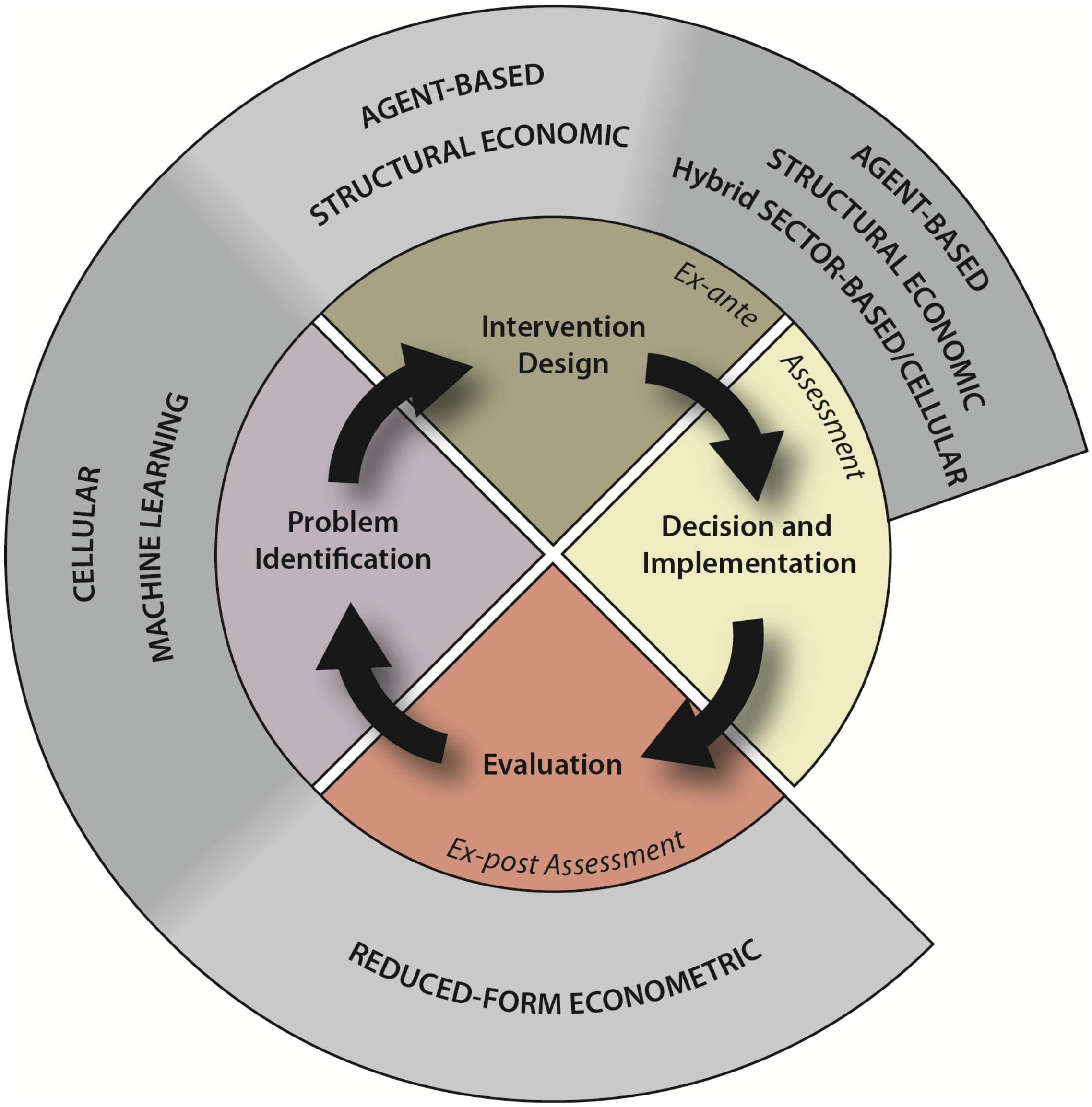


Figure 2.2 Land change modeling approaches (outer circle) placed within the context of the policy- and decision-making cycle (inner circle).
SOURCE: modified from Verdung, 1997.

(e.g., through creation of protected areas) or where baselines based on extrapolating past trends are needed for ex ante assessment, but their comparative advantage is in problem identification. To consider interventions that affect agent behaviors or might generate market feedbacks that have spillover effects on other components or locations in the land system, the richer behavioral specificity of agent-based and structural economic models provides a basis for exploring the structure of the land system and the interactions inherent in it, and exploring dynamics that might benefit from intervention. For example, links between household inequality and environmental outcomes can be explored to identify the reasons for and opportunities to improve both. The process specificity of these modeling approaches is usually needed to weigh the effects of alternative interventions.

In moving to a decision about some policy or other action, structural economic models, including both sector-based and spatially disaggregate as well as agent-based models, and hybrid models provide capabilities that can be exploited for assessing the possible effects of the policy, ex ante. For example, the GTAP model (Hertel, 1997), which is a static multi-region, multi-sector, CGE model, was used to evaluate the implications of biofuel mandates for land use demand both within the United States and internationally through the possible effects on the prices of food commodities (Keeney and Hertel, 2009).

Once policies or decisions have been implemented, the need for evaluating the effects of these implementations, ex post, is often quite effectively met through use of reduced-form economic models that estimate the magnitude of the effect of the intervention, usually by comparing observable outcomes either before and after the intervention or in an intervention area and some comparable location. For example, Andam et al. (2008) used reduced-form econometric methods to evaluate the effectiveness of protected areas in reducing deforestation globally by estimating the effects of the protected areas on deforestation rates in comparison with those found in areas in close proximity to protected areas.

Understanding the underlying structures, assumptions, and data requirements of different modeling approaches is critical to understanding their applicability for various scientific and decision-making purposes. This review provides a framework for comparison of multiple modeling approaches in relation to specific objectives. The next section of this report outlines opportunities and needs for advances that will improve modeling capabilities into the future.

3

Improving Land Change Modeling

The various approaches employed in land change models (LCMs) have emerged from multiple disciplinary traditions, and future progress in improving LCMs will likewise draw on multidisciplinary developments. At this point in the development of LCMs, as a category of models that bridges and couples among the dynamics and processes of social systems and natural systems, the diversity of model types has served a number of scientific and practical goals. The growing demands on these models within the science of sustainability and for integration with environmental models require that the community of model builders and users take advantage of a number of opportunities to advance both the theoretical and empirical grounding of models. We identify opportunities in modeling that derive from the potential for better models, better use of data and cyberinfrastructure, better community infrastructure for LCM developers and users, and better use of best practices in model evaluation.

OPPORTUNITIES FOR ADVANCES IN LAND CHANGE MODELS

Advancement of Process-Based Models

The approaches on the pattern end of the pattern-process spectrum will continue to provide useful service in a number of scientific and practical settings, as outlined in Chapter 2. However, a number of new applications of models involving developing and evaluating innovative land-based policies, exemplified, for example, by payments for ecosystem services (PES) and REDD+ strategies for curbing deforestation and land degradation while providing income for forest-dependent communities, demand a stronger process (i.e. theoretical) basis for LCMs. The theory, data, and methods needed for developing process-based models are arguably less well developed than those needed for models based on patterns. Modeling approaches are required that can be used to evaluate how these policies will influence human behavior and in turn affect land cover and human well-being (Nelson et al., 2009). For example, PES schemes pose a challenge for modeling because they alter the economic incentives to influence current land use behavior and thus land trajectories. Also, evaluations of REDD+ policies require an estimation of baseline emissions, e.g., the amount of deforestation that would happen in the absence of a new policy. While these baselines have tended to use machine learning and statistical models (i.e., data-based models) to project past rates of deforestation, process-based baselines could include demographic and economic changes that might affect future deforestation (Huettner et al. 2009). Additionally, evaluations of new policies require models that represent behavioral responses to new incentives or constraints, both of which require some understanding and representation of process. Because such policies tend to address only a few of a multitude of interconnected outcomes (e.g., numerous ecosystem services and human well-being factors), better process representation is needed to evaluate possible unintended consequences from such policies.

Because they account for the underlying decision-making processes of agents that determine land change outcomes, process-based models can be used to advance understanding of how human actors respond to changing environmental, economic, or policy conditions and to simulate policy scenarios of the impacts of a hypothetical policy change on land use outcomes. Process representations are particularly important when modeling complexity in land-change processes in which feedbacks can arise from interactions that are both within and between the socioeconomic and biophysical systems.

Despite meaningful advances, more work is needed to further develop process-based models that are consistent with theory, empirically verifiable, and useful for policy. Many efforts to date have focused on one or at most two of these goals, and fewer if any have accomplished all three goals. For example, structural econometric models are derived from economic theory and estimated using real-world data, but they are largely static and can only incorporate limited forms of spatial heterogeneity. Agent-based models are often specified using real-world data, can incorporate many more forms of agent and spatial heterogeneity, and are designed to step through time, but they are often ad hoc in their representation of market and other mechanisms and often lack the empirical or theoretical grounding for some of the assumptions that are necessary to operationalize a given model. As outlined in Chapter 2, it is possible to develop spatial equilibrium economic models that incorporate some form of dynamics and to develop agent-based models that are consistent with microeconomic foundations. In some ways, these different approaches to process-based modeling are converging and there are additional gains to be had from continuing to work toward narrowing the gap. For example, because of their added flexibility, agent-based models can be useful in testing the maintained assumptions of economic structural models by comparing model predictions from long-run spatial equilibrium with a short-run constrained equilibrium subject to additional constraints such as incomplete information or borrowing constraints. The process of reproducing the results of analytical models with a computational model is sometimes referred to as “docking” and has been shown to be a useful way to build agent-based models that relax assumptions while building on solid theoretical principles (Brown et al., 2004).

By representing agents’ behaviors and their behavioral responses to policy, process models permit researchers to generate and compare predictions of land changes under baseline and alternative policy scenarios. The quality of such scenarios and predictions is limited by the maintained assumptions and process details in the models. Research on cognitive processes demonstrates substantial heterogeneity among agents in terms of their formation of values, preferences, attitudes, and norms and how these preferences are modified by environmental change (Meyfroidt, 2012). Additionally, theory and empirical research on forward-looking behavior underscores the importance of accounting for heterogeneous expectations over future outcomes that influence agents' decisions in the current period (Irwin and Wrenn, 2013). Incorporating these new theoretical insights is critical for improving the structural validity and predictive capability of LCMs, and requires improved model formulations and better data on individual agents and their decision-making processes over time and at spatial scales commensurate with the individual agents. We address the issue of data availability in the section on opportunities in observation.

Cross-Scale Integration of Land Change Models

A major goal of the environmental science community is to develop a predictive and process understanding of the interactions of land change dynamics with climate; ecosystem biodiversity; and the cycling of water, carbon, and nutrients. The need for this understanding is manifested at scales ranging from parcels to the globe and is a central element connecting a set of scientific and policy groups recommendations such as the Grand Challenges in Environmental Science by the National Research Council (NRC, 2001). This challenge emphasizes both research to elucidate the primary feedbacks between socioeconomic, geophysical, and ecosystem processes critical to the coupling of land, water, and ecosystem change, and the ability to reconstruct and forecast historical and future scenario trajectories. To make advancements on these goals, two types of model coupling are required: coupling of LCMs at multiple scales, and coupling LCMs with other types of models. This subsection addresses the former; the next subsection addresses the latter.

Globalization is having the effect of coupling global- with local-scale drivers of land change, and land use decisions are increasingly driven by factors in distant markets in addition to local-scale factors (Erb et al., 2009; Seto et al., 2012). There is a growing separation between the locations of production and consumption of land-based commodities, including carbon stocks. Consumers outsource their land use to other regions or countries and a virtual land trade develops. In addition, land use is affected by remittances sent by migrants, the specific organization of global commodity value chains, channels of foreign investments in land, the transfer of market or technological information to producers via a diversity of networks (from farmer associations to Internet and cell phones), and the development and promotion of niche commodities that target narrow but wealthy market segments with high-value commodities produced in limited quantities. Modeling such *teleconnections* (or *telecoupling*) and network interactions is a major challenge that requires analytical methods that link multiregion input-output models with regional and local-scale models of land-based decision making (Würtenberger et al., 2006) and representations of social networks.

While the sector-based approaches outlined in Chapter 2 provide a framework for modeling interregional flows of capital, materials, and people, they represent entire sectors within entire regions as single representative agents. Such representations preclude incorporating an understanding of how heterogeneous decision-making strategies affect demand and supply of products and inputs (including land), and how interactions among actors within a given sector or region might produce particular patterns of production or consumption (Rounsevell et al., 2012). For example, the emergence of a cluster of activity within a region, like that which occurred in the information technology industry within the Silicon Valley of California and manufacturing in Shenzhen, China, can produce efficiencies and increasing returns to investment and create demands for land that are not represented or in quantities not reflected in aggregate models (Arthur, 1994). The spatially disaggregated economic and agent-based models provide a means to represent heterogeneity and interactions, but they have not yet been developed at scales that permit representation of global-scale flows. Although it is possible that such models could be developed, parameterized, and simulated at global scales, it is also possible that a scaffolding of modeling approaches, which specifies which models are used to pass different kinds of information among different scales of representation, will be a more efficient and effective for representing global-to-local interactions. Possible directions include either combining the aggregate and finer-scale models to link feedbacks and interactions at the finer scale within the context of global-scale flows, or using experiments at the fine scale to evaluate nonlinear dynamics that emerge and represent important sensitivities of results at the coarser scale.

Cross-Scale Integration of LCMs with Other Earth System Models

For years, models of a variety of environmental processes have taken land cover and land use as inputs to condition model parameters or set internal fluxes or states, and they generate information that may in turn condition land management decisions and feed back to land change. Examples include models of Earth surface processes like exchange of water, energy, carbon, and nutrients with the atmosphere that are critical to weather and climate prediction (e.g., Bondeau et al. 2007; Lawrence et al. 2011); watershed models that generate flow, nutrients, and sediment to receiving water bodies (e.g., Ray et al. 2010; Bulygina et al. 2012); and ecological patch dynamics of growth, succession, and disturbance (e.g., Desai et al. 2007; Thompson et al. 2011). By coupling these models with LCMs, the ability to predict and understand the direct and indirect effects of land management decisions and policies on the trade-offs at short to long time scales on ecosystem services (e.g., food and fiber production, water regulation, maintenance of biodiversity, and carbon storage (Lapola et al., 2010; Nelson et al., 2009; Wiley et al., 2010) is improved. In the short term, or in areas not experiencing significant change, land change is typically considered a static model input and a coupling with dynamic LCMs is not required. However, interest in long-term forecasting requires some ability to couple models to represent feedbacks between environmental and land change dynamics. The ability to set up and carefully specify different scenarios facilitates the development of verifiable models that provide utility to policy makers and decision makers.

From a systems perspective, the degree and completeness of coupling of environment and land change processes needed within a model (or set of linked models) is dependent on which processes are included as endogenous dynamics, and which are prescribed as exogenous drivers and boundary conditions. More comprehensive models, representing more endogenous processes, may be required to evaluate and forecast trade-offs and interactions between different ecosystem services and land change, both in the short term and over the multidecadal time scales envisioned in climate change mitigation and adaptation. Examples of situations where land change produces trade-offs include those between carbon sequestration and freshwater supply from land conversion to plantation forestry and natural regrowth (e.g., Farley et al., 2005) and between low-density zoning for watershed protection and septic-derived nitrogen loading (e.g., Shields et al., 2008). Current LCMs use a range of simple to complex methods to estimate biophysical outcomes or consequences of land change, such that choices about model parsimony, comprehensiveness, and complexity affect the richness of environmental information that can be provided for decision makers. In any coupled model, a balance of the different components in terms of degree of complexity and data demands is preferred to promote representation of critical feedbacks.

The research and operational environmental models which use land use and land cover (LULC) as *one-way* inputs to determine model parameters or set internal fluxes or states are numerous. LULC are typically used as categorical variables with class-specific attributes that are used to generate model parameters. This is done either by assignment from look-up tables by LULC category or by specifying class-specific equations that may use additional ancillary information (e.g., remote sensing radiances). Well-known examples include the use of LULC to assign or calculate properties including surface albedo, impervious area, or leaf area index (LAI). Human behavior (e.g., irrigation, fertilization, harvesting, and conservation practices) may also be set by land classes, or it can be attributed separately using associated demographic and economic information. The distinction, and confusion, between land use and land cover as inputs to these models is important and represents an area where data advances, described below, can advance the effectiveness of models. While land-cover inputs to biophysical models are common, the dynamic coupling of LCMs to these model is less so.

Opportunities for environmental processes to provide *one-way* inputs to LCMs also exist but have been less commonly employed. At the scale of individual land patches, a set of land cover classes will be developed within an ecological successional trajectory following disturbance or other forms of land conversion (e.g., agricultural abandonment, timber harvest or fire). These functions may use simple, rule-based succession trajectories (e.g., through Markov chains). However, there is significant potential to better couple process-based growth and succession models to represent both the processes of environmental change and feedbacks with land use and management. A set of models ranging from growth and yield curves through complex community ecological and biogeochemical models (e.g., Biome-BGC, CENTURY, ED, LANDIS) were designed to simulate ecosystem dynamics within prescribed species or life-form classes, or to simulate ecological population dynamics. Modeled changes in either ecological patch attributes such as standing biomass, water and nutrient availability, or habitat quality can then be used to condition land conversion processes. These models can also be sensitive to local edaphic or microclimate conditions, such that patch-specific trajectories can vary in space and time rather than following a domain-wide set of common, prescribed rules. As such, the heterogeneous information conditioning patch- or parcel-scale conversion can influence more spatially variable and environmentally coupled LCMs.

A more complete analysis of interactions between altered biogeochemical, hydrologic, and other ecosystem services and land change would incorporate *two-way* coupling through feedbacks. These feedbacks could be realized through altered supply and demand of critical ecosystem resources (e.g., water, food, and carbon credits) or from regulatory response to degraded air or water quality. While more comprehensive models would have the advantage of endogenizing these feedbacks, current understanding and ability to represent these interactions within coupled models are subject to high uncertainty, especially over longer time scales. Full two-way coupled models, in which land and environmental systems coevolve, are beginning to emerge. Schaldach and Priess (2008) reviewed a set of models that have been used to endogenize and couple environmental and land change processes. Model structures range from loose coupling with information passing between separate models (e.g. Claessens et al., 2009) to more tightly coupled models in which common variables are processed by different modules or through unified equation sets, providing close feedback between environmental and socioeconomic processes associated with land change dynamics. Maintaining dynamics through the full system, rather than prescribing either the land change or environmental components of a coupled model, necessarily increases model comprehensiveness and complexity, and so a challenge is to balance and manage code complexity through a combination of prioritizing process and feedback selection and simplifying the component models, and by more sophisticated informatics. Other challenges include the need to determine how an output from one model relates to the input of another, the lack of standard scales in coupling (and associated aggregation/disaggregation problems), and the assessment and management of uncertainty from one model in another (e.g. Pijanowski et al. 2011).

One approach to implementing full coupling between LCMs and environmental process models would be through operationalizing the conceptual model developed by the Integrative Science for Society and Environment (ISSE) (Collins et al., 2008), which links human outcomes and activities with ecosystem functions through the identification and management of ecosystem services. As an example, a set of land models (e.g., the Patuxent Land Model, Everglades Land Model) combined land valuation and conversion over different uses, with simulation modules for coupled water, carbon, and nutrient cycling. Land cover class has a first-order impact on ecosystems by setting model parameters. Because land valuation can be subject to simulated ecosystem components, such as the productivity of agricultural land, a local feedback on decision making is developed at the parcel level, such that less productive agricultural land will have a greater probability of being developed. Extension of these models to quantify values of ecosystem services, and measures of human well-being (e.g., Costanza, 2000) developed at landscape to regional levels as a result of the coupled dynamics, could serve as a basis to complete the major feedback look in the ISSE conceptual model.

A number of LCMs can include this form of local feedback of ecosystem to parcel-level decisions on land conversion and, by extension, influence neighborhood-scale patterns. Larger-scale feedbacks of ecosystem processes to socioeconomic decision making can occur from runoff quantity and quality, which can initiate institutional responses and regulatory constraints on development and economic activity, or from land surface–atmosphere exchange through simulated emissions of heat, vapor, greenhouse gases, and other pollutants. This type of feedback would be a cumulative one derived from aggregated ecosystem patch behavior at larger regional to global levels. Such a feedback would also need to be endogenized within the model at these larger scales through representation of institutional actors that respond to observed changes by constraining land management, including land conversion and economic activities. To represent the appropriate spatial units at every scale and across different kinds of processes, one option is to use a "class containment hierarchy" in which fine-resolution land patches are explicitly connected and progressively contained and linked within larger-scale units (e.g., hillslopes, subcatchments), defined as connected component regions that maintain class-specific common attributes and process dynamics. Hierarchical frameworks linking processes over multiple scales can be used to resolve fine- to larger-scale interactions.

Bridging LCMs with Optimization and Design-Based Approaches

The land change models reviewed in Chapter 2 are described as *positive* models that seek to explain and predict changes in land use and land cover using either a process-based or a pattern-based modeling approach. In contrast, policymakers can also benefit from a *normative* evaluation of these predicted outcomes: Given a choice among a set of possible policies or designs, which policy will generate a landscape pattern that is "best" in some sense for society? Various evaluation methods have been developed in urban planning, geography, economics, and related disciplines to assess alternative land use or land cover outcomes. The challenge is to develop and use LCMs at scales relevant to design and to connect design to patterns on the landscape, and to use optimization approaches together with the LCM approaches we describe in Chapter 2. For example, one study linked an optimization model with a cellular automaton simulation to generate future projections that could be optimized for and evaluated on how well they met specific planning objectives (Ward et al. 2003). Other work has used optimization approaches based on LCMs coupled with watershed models to help in identifying and locating land uses that reduce watershed impacts (Tang et al. 2005; Maringanti et al. 2009). An important challenge is that the optimization approaches widely used in spatial sciences, from land use and ecosystem service planning (e.g., Polasky et al., 2008; Roetter et al., 2005; Seppelt and Voinov, 2002; Stewart et al., 2004) to site selection for businesses (Church and Murray, 2009), are extremely intensive computationally.

Marxan, a piece of widely used conservation planning software, provides a good example of a normative approach based on optimization to evaluating land use alternatives. This software is designed to solve complex conservation planning problems in landscapes and seascapes (Watts et al., 2009). Whereas earlier versions of Marxan mainly focused on the optimal allocation of reserved areas for nature conservation, later versions were extended with zones, providing land use zoning options in geographical regions for biodiversity conservation. The software allows any parcel of land to be allocated to a specific zone. Each zone then has the option of its own actions, objectives, and constraints, with the flexibility to define the contribution of each zone to achieve targets for prespecified features (e.g., species or habitats). The objective is to minimize the total cost of implementing the zoning plan while ensuring a variety of conservation and land use objectives are achieved. In one application, Wilson et al. (2010) used Marxan to prioritize investments in alternative conservation strategies in East Kalimantan (Indonesian Borneo).

Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) is a spatially explicit software-based tool developed by the Natural Capital Project (http://www.naturalcapitalproject.org) that provides a means of comparing trade-offs among ecosystem services by quantifying the value of natural capital in biophysical and economic terms. The modeling process starts with stakeholder-defined scenarios of LULC changes in the study region of interest. Given these scenarios as inputs, InVEST calculates the changes in targeted ecosystem services (e.g., including biodiversity conservation, water quality, and commodity production levels) for each scenario. The approach provides a means of quantifying ecosystem services in a spatially explicit manner and analyzing trade-offs among alternative scenarios or policy options, including how payments for ecosystem services can alleviate trade-offs in which private markets result in an insufficient provision of ecosystem services by landowners. For example, Goldstein et al. (2012) applied InVEST to evaluate the environmental and financial implications of alternative land use development plans for the largest private landholder in Hawaii, Kamehameha Schools. They examined the implications of these alternative land use scenarios for multiple ecosystem services, including biofuel feedstocks, food crops, forestry, livestock, and residential development. They predicted the changes in these ecosystem services for each land use scenario and then used observed prices or parameter estimates of nonmarket values from the literature to translate changes in ecosystem services into monetary benefits and costs. They found, for example, that diversifying agriculture can generate additional financial returns and contribute to climate change mitigation through increased carbon storage, but that trade-offs exist between carbon storage and water quality. Based on this information, the private landholder developed a land use plan to meet private financial goals that also generated societal benefits through climate change mitigation, improved food security, and rural economic development. These calculations in InVEST could also be thought of as objectives to be attained in an optimization process.

Clear synergies can be achieved from integrating positive LCMs with normative methods such as Marxan and InVEST, and traditional design approaches, which could provide a means for generating and evaluating land change scenarios and policy or management mechanisms that meet some specific goals. Positive models have the capacity to explain or predict land change patterns and processes that are associated with specific trends or policy changes and normative models elucidate the trade-offs associated with predicted outcomes and identify desirable outcomes considering those trade-offs. When used in combination, LCMs and normative approaches could be used in analyses of the trade-offs relative to multiple objectives generated by the change. Process-based LCMs and normative approaches together can provide meaningful guidance to policy makers regarding the potential benefits and costs of a policy by describing the predicted effects of a policy on land change. Data-based LCMs integrated with normative approaches can also be used to explore how projected land changes compare to some specified objectives and possible ideal outcomes (Seppelt et al., 2013). Because many existing optimization models include spatial patterns as explicit objectives, combined analyses of positive and normative models might be useful to fully incorporate the shape, size, distribution, and connection among different land units into the analyses of land system dynamics and trade-offs. Advances in combining positive and normative approaches will likely require adaptations of both, extending optimization approaches, like Marxan, to include dynamic land systems and adapting LCMs to couple more directly with the environmental and other models that are used to evaluate and quantify outcomes, using tools like InVEST.

OPPORTUNITIES IN LAND OBSERVATION STRATEGIES

The second set of opportunities is not necessarily associated with the availability of data, but rather in how the enormous quantity of new data can be incorporated into LCMs, how land change modelers can learn about and adapt modeling approaches to use these new data sets, and how land change modelers can help inform the development of image-processing algorithms and data collection schemes that can generate products for the next generation of land change models. This opportunity identifies both gaps in the availability of data for LCMs, particularly in limiting the characterization of processes of land change, and ways to fill those gaps. Additional opportunities are presented through new cyberinfrastructure, discussed in the next section. These challenges have been mentioned by others and some progress towards meeting these challenges is being made. However, the committee believes that more progress on these topics is needed to mainstream these advances into LCMs and respond to user-requirements.

Improved Capture and Processing of Remotely Sensed Data

New data sets are required that can provide information on the dynamics, stationarity, and complexity of land and land-related processes. There has been a significant increase in new satellite and airborne sensors, which has resulted in an explosion of data and new analyses, but the development and application of models has not kept pace with developments in data. Large data sets provide new opportunities for land modeling but create various needs for automated processing. Methods that were developed for analysis of small- to medium-sized sets of images or similar packages of related data need to be adapted to handle long time series and larger geographic extents, often at finer spatial resolutions. For example, new image-processing algorithms that use objects rather than pixels as the unit of analysis may provide new types of data opportunities to link satellite-based LULC information with land management information (Pasher and King, 2010; Zhu and Woodcock, 2012), and to develop models that operate on patch or parcels rather than pixels, which are the most common unit of analysis in LCMs. High-spatial-resolution data, such as that provided by QuickBird, are able to provide fine-scale habitat and plant diversity information (Hall et al., 2012) and active sensors, like LiDAR, provide canopy structural information (Ardila et al. 2012; Walton et al. 2008; Lehrbass & J. Wang 2012; Morsdorf et al. 2004; Sohn & Dowman 2007), both of which create opportunities to develop LCMs that generate land-cover outputs with detail that goes beyond nominal categories. Significant efforts at mapping LiDAR during leaf-off periods is supporting DEM creation and flood management purposes, but more leaf-on LiDAR data is needed for these applications related to vegetation canopy structure. Additionally, new and improved image-processing algorithms are providing new information about land use and land-use characteristics, such as land-use intensity (Franke et al., 2012). These algorithms can be deployed to develop data-based LCMs that are more directly sensitive to land use.

Essential to future progress in LCMs is the continuity of satellite-, airborne-, and survey-based observations that build on the existing record of Landsat, as well as national surveys and censuses, in order to estimate and calibrate LCMs. A majority of respondents to the committee's informal questionnaire mentioned the importance of capturing historic data, such as aerial photos and old land records, as well as maintaining satellite mission continuity. With the Landsat record now spanning more than 40 years and the entire archive now available free of charge, new algorithms are being developed that utilize the entire (or most of the) time series. These high-frequency temporal observations provide new types of information on land cover and land use, such as disturbance (Baumann et al., 2012; Stueve et al., 2011; Zhu et al., 2012) and land-use intensity (Maxwell and Sylvester 2012), which were not available with the less frequent observational data commonly used prior to the opening of the archive. In addition to creating opportunities for new data inputs to LCMs, the higher temporal frequency of images permits the kind of temporal analysis used to describe LULC temporal dynamics at coarser resolutions (Eastman et al. 2009; deBeurs and Henebry 2010) and at moderate to fine resolutions. In combination with the growing length of the archive of Landsat images, these new analyses will facilitate a better empirical understanding of spatial and temporal non-stationarities in land-change processes, which can ultimately improve our understanding of key variables and processes that need to be incorporated in LCMs. Furthermore, the higher frequency of available observations will drive demand for restructured LCM frameworks, especially for those that are more data-based (i.e., statistical, machines-learning, and cellular approaches), and that accommodate more frequent observations and more recent observations, perhaps through use of data assimilation approaches (e.g., Rodell et al. 2004). These approaches have not been used with LCMs to date.

Historical aerial photo data sets offer the potential to extend existing records of land cover and its change even further into the recent past, before the availability of satellite imagery (e.g., Sylvester et al. 2013). Object-based analysis and machine learning algorithms are particularly promising technologies to create land use information from historical photos. Contextual information from object-based approaches promises to improve classification of aerial photography, despite inconsistent spatial and spectral information in these data (Laliberte et al., 2004). As longer time series data become available, e.g., greater than 70 years, the challenges and opportunities of modeling land change through periods of structural economic and technological change becomes very real. While Chayanovian and Boserupian theories of development provide a starting point for understanding livelihood changes on these time scales, few structural models exist of how land systems evolve over longer time frames, though new models could build upon theoretical and empirical work in economic and demographic literature (e.g., Galor and Weil 2000; deSherbinin et al. 2008). While longer term economic and population forecasts are already incorporated as inputs to a variety of LCMs that rely on statistical approaches to allocate the land implications of these changes spatially (e.g., Bierwagen et al. 2010), endogenizing these changes in longer-term structural models would permit a better representation of complex dynamics and feedbacks between land use and livelihoods.

Remotely sensed data are being used in new ways to generate socioeconomic information, such as the use of the nighttime lights product to estimate variables related to energy consumption (Zhao et al., 2012; Kiran Chand et al., 2009; Townsend and Bruce, 2010; De Zouza Filho et al., 2004), and economic activity (Chen and Nordhaus, 2011; Henderson et al., 2012). By providing a means to estimate key socioeconomic variables in spatially and temporally explicit ways, these new analyses provide a basis for new approaches to parameterizing LCMs. For example, data on energy use or economic activity could be used to better represent a diversity of livelihoods and land-use strategies, which could convert to better representations of how and where land is likely to change.

The growth of small Earth observation sensors is another important development in remote sensing. The constellation of newer and smaller satellite and airborne platforms includes many from private companies and private-public partnerships such as Specim hyperspectral airborne sensors (Eagle, Hawk, Owl, and Dual) from Finland, Itres Compact Airborne Spectrographic Imager family of sensors from Canada, and Proba-1 from the European Space Agency, to name only a few. Hyperspectral sensors provide the opportunity to develop richer biophysical attributes of the land surface that could provide new measurement inputs to LCMs. For example, because these sensors are sensitive to canopy chlorophyll and nitrogen (e.g., Ebbers et al 2002; Kaye et al. 2005), it may be possible to use them to infer information about variations in land management behaviors, which are hard to measure. Some of these smaller satellites are configured for specific applications in specific regions. For example, the Disaster Monitor Constellation of small and low-cost Earth observation sensors developed by Surrey Satellite Technology Limited in the United Kingdom can be used for land monitoring at high spatial resolutions, which include NigeriaSat-1, NigeriaSat-2, NigeriaSat-X, Beijing-1, and UK-DMC-1, among others. The Advanced SCATterometer onboard the Metop satellite is a follow-on to the European Remote Sensing scatterometers and provides a soil moisture product at coarse spatial resolutions (25 and 50 km) and at nearly daily repeat cycles (Brocca et al., 2010). Soil moisture retrieved in this way could be used as an input to LCMs, for example to help parameterize a model that includes decision to irrigate as one of its processes.

Integration of Heterogeneous Data Sources

An important challenge to making the most of remotely sensed data for use within LCMs is to integrate them with a variety of heterogeneous data sets. Land change information at a variety of spatial and temporal resolutions can be integrated with socioeconomic and biogeophysical data for coupling of LCMs and other types of models such as models of climate change, ecosystem services and biodiversity, energy use, and urbanization. There is also a need to go beyond LULC in LCMs and incorporate other dimensions of land. As discussed above, new remote sensing sensors and approaches are showing promise in better retrieving land-cover dynamics, land-use variables like intensity, biophysical variables like plant nutrient contents and soil moisture. Data fusion approaches have shown promise for these purposes (Lunetta et al. 1998; Sun et al. 2003; Mutlu et al. 2008). Other variables, including land function, land use density, land tenure, land management, and land value are difficult to characterize on the basis of remote sensing data alone. *Land function* includes the provision of goods and services related to the intended land use as well as benefits from aesthetic values, cultural heritage, and preservation of biodiversity. Information on *land use density*, though it can be estimated from nighttime lights images, might benefit from additional data about residences, buildings, or employment. LCMs increasingly need to represent information and processes about *land management decisions*, often at high temporal resolutions, such as crop types, irrigation, fertilizers, and urban development patterns. While soil moisture and canopy nutrients can help, data on land management decisions (e.g., permitting new urban development) and policies (e.g., zoning and stormwater incentives) need to be available at different administrative levels (e.g., local, county, and regional land use plans). Poor availability of spatially explicit ecological data, such as crop pollination, timber production, and land-based carbon resources, constrains assessments based on ecosystem service models like InVEST. In all of these cases data from remote sensing are useful, but insufficient sources that need to be combined with other available data. Combining and leveraging various data sources to create hybrid data products that draw together remotely sensed, spatial, and social data can create new types of information products.

To support further developments in the use of remotely sensed data to estimate aspects of the land surface that have greater relevance to assessment of both its human and ecological value, and to make these data available for adaptation within LCMs, ongoing in situ observations and survey programs are needed on all of these topics. Additionally, though data on land value and land ownership cannot be collected through remote sensing, they are often available locally in the developed world but more inconsistently available in the developing world. Unfortunately, no consistent program for compiling the data exists, so the research community also lacks good, reliable access to data on land value and land ownership (i.e., cadastral data). Opportunities for compiling land parcel data have been outlined elsewhere (NRC, 2007), and data on land values, based on transactions, can be collected and compiled (e.g., Zillow and Trulia), but these data remain an expensive component of many LCM projects. Understanding and communicating the limits of data availability and their implications are important throughout the modeling process.

Data on Land-Change Actors

Land change is the cumulative result of the decisions and interactions of a variety of actors—households, firms, landowners, and policy makers at local, regional, and global levels. Current models, as well as their theoretical and empirical bases, are limited to some extent by their use of (a) aggregate data that miss important sources of spatial heterogeneity; (b) cross-sectional data that prohibit causal identification; and (c) a dearth of microdata on the characteristics, preferences, and decision-making processes of households, firms, policy makers, and other agents whose actions determine land change outcomes. These limitations are especially marked for the process-based approaches such as structural economic and agent-based. Better data on these actors and their beliefs, preferences, and behaviors is critical to improving the theoretical underpinnings, structural specifications, the predictive ability, and the usefulness of LCMs in evaluating the consequences of alternative policies. These data should be spatially explicit and available for multiple points in time so that they can be used to specify dynamic spatial models of land change processes.

Despite the increasing availability of spatial data on land change, data on the individuals whose choices and interactions generate observed land changes are often missing. For example, though parcel-level property tax data have been increasingly used in LCMs, these data omit information about households, for example, income, race, presence of children, education, and other variables that influence household location choices. Researchers have compensated by combining the parcel data with data from the U.S. Census Bureau on household characteristics, but these data are only publicly available at a more aggregated spatial scale (block group or tract) and traditionally were available only every 10 years. Since 2006, the U.S. Census Bureau has published the American Community Survey, which provides data on a subset of household characteristics for a sample of households in the United States. The data are produced annually to represent an aggregation of observations of a period of years, which depends on the spatial scale of observations. Although this approach adds temporal dynamics, it is achieved through temporal averaging which limits its usefulness. Creating data sets that contain spatial data on individual characteristics and behaviors over time will require considerably more effort and resources.

In the absence of a systematic and purposeful data-collection effort on land change actors, many ad hoc approaches to generating these data have emerged. Several of these approaches are quite promising. The approaches that have been used to collect data on agent characteristics, decision processes, and behaviors represented in agent-based models include surveys, field and laboratory experiments, participant observation, role-playing games, and inference with statistical methods (Robinson et al., 2007), most of which involve significant expense. An innovative example of the latter is the use of restricted microdata that are available from some government agencies. For example, the U.S. Census Bureau operates 14 secure research data centers located in different parts of the United States that provide opportunities to work with restricted-use microdata on households and firms. Restricted access to confidential data on farmers and farming operations in the United States is available through the U.S.

Department of Agriculture (USDA). These data permit new research questions regarding the underlying economic or behavioral process to be studied by providing additional information about individual characteristics and location. For example, Kirwan (2009) used individual data on farms and farm rental rates to identify the effect of government agricultural subsidies on farm rental rates. The individual-level farm data are critical to identifying the causal effect, which otherwise would be impossible to separate from correlated unobserved variables using more aggregate data. Finally, there are examples of innovative models estimated with microdata from a survey. For example, Conley and Udry (2010) modeled the role of technology spillovers in influencing agricultural production decisions in rural Ghana. These authors collected intricate details about the neighbors with whom pineapple farmers in Ghana communicate and what they share with each other about their production practices. They then used these microdata on social interactions to estimate a microeconomic model of technology spillovers based on social learning. Game-based approaches, participatory mapping, and participant observation approaches support more deductive approaches that avoid the major assumptions about human behavior involved in statistical modeling (e.g., Castella et al., 2005). These approaches are generally applied for smaller areas and may be challenging to scale to larger areas.

Making Systematic Land Use Observations

In addition to consistency and continuity provided by remotely sensed observations, the reliance of LCMs on heterogeneous data, many of which are not completely observable remotely, means that a healthy LCM enterprise relies on robust and ongoing on-the-ground observations of multiple dimensions of natural and human systems. Because survey programs on land characteristics, like those on water, are divided among multiple agencies and geographies, integrating data for understanding and predicting changes in the land system can be particularly challenging. For example, in the United States, data on forests are collected by the USDA Forest Service through its Forest Inventory and Assessment, data on farms through the Census of Agriculture, data on demographics through the Census Bureau, and so on. All agencies use different sampling schemes, temporal return intervals, and geographic aggregation units.

The Natural Resources Inventory (NRI), developed and implemented by the Natural Resources Conservation Service, has been the only national-scale, repeated sample of land use, but it was not designed or intended to serve that purpose. Nonetheless, important research on the drivers of land use change has resulted from that program (Lubowski et al., 2006). The loss of continuity in fine-scale NRI land use data is a setback for forecasting land change in the United States at fine scales.

For these reasons, the committee obtained information from the community about the potential need for a national land observatory, or a national survey of land resources. The idea was raised at one public meeting, where it was discussed constructively by participants. We followed this discussion with an informal questionnaire that reached members of the LCM community. Over 100 responses to the questionnaire revealed support and interest in using data from such a survey. Although beyond the scope of this report to outline the design for such a survey, we conclude that a program to collect spatially referenced data with linked records on land patches, land parcels, and land users sampled through a purposive design and maintained through repeated waves over time presents a significant opportunity for the LCM community. Such a program would facilitate greater understanding of land change processes, would allow hypotheses to be tested, and would improve our predictive ability.

OPPORTUNITIES IN CYBERINFRASTRUCTURE

A number of the challenges noted above have the potential to find solutions through contemporary advances in cyberinfrastructure. In the following sections, two areas are described in which cyberinfrastructure advances represent potential opportunities for land change modeling.

Crowd Sourcing and Distributed Data Mining

A key data need for better construction, calibration, and validation of structural models is in the area of microdata on agents, especially for process-based LCMs. The ability to collect and analyze very large amounts of data on individual behaviors, much of which is referenced in time and space, has grown tremendously over the past decade. Examples include point-of-sales data on individual purchases by consumers, location-aware technologies that track individuals in space and time, and Internet activities that reveal social networks. Additionally, computationally and labor-intensive processes are increasingly being conducted by distributed groups, assisted by the increases in the computational power of computers alongside high-speed Internet access. Lazer et al. (2009) viewed this development as an emerging computational social science that is based on researchers' ability to harness these data. However, as Miller (2010) discusses, the privacy and propriety issues are not trivial and are mostly unresolved.

Additionally, the LCM community could benefit from distributed data collection facilitated by Global Positioning System– and Internet-enabled mobile devices. A number of recent projects have successfully combined data from traditional sources with geospatial and other data that are crowd sourced from a relevant population and illustrate how data-collection efforts might be structured to facilitate model parameterization. Citizen-contributed data supported the implementation of Ushahidi in Haiti following the 2010 earthquake, which helped plot at least 4,000 distinct disaster events (Zook et al., 2012), where universities and nonprofit agencies played important roles in disaster response. Information was provided by volunteers and aggregated for visualization, use, and analysis. Micropayments for microtasks, following on the model of Amazon's Mechanical Turk, have also shown promise as a means for data collection (Kittur et al., 2008), including social survey data. These data could be used as inputs on the heterogeneity of actors in agent-based approaches. Statistical and econometric approaches to parameterizing the behavior of land-use actors could take advantage of these data, but issues related to uncertainty in these data require further investigation (Flanagin et al. 2008). Given the potential for large volumes in these data, and problems associated with unknown and variable data quality, data mining and machine learning approaches may be the most promising approaches for extracting model inputs from them. Extensible data tools on mobile devices have also been used to enhance the participatory nature of efforts to collect microdata on agents. Google Maps, and other cloud-based mapping technologies, are already being used in environmental monitoring projects to create geospatial data sets that are coproduced by the public and scientists (Connors et al., 2012; Goodchild, 2007). Examples in international agriculture include the Avaaj Otalo study, which used an interactive voice forum for rural farmers (Patel et al., 2010); another study used mobile phones for collecting information at various points in the coffee production process for small farmers (Schwartzman and Parikh, 2007); and the Digital Green project delivered targeted information to marginal farmers through participatory networks (Gandhi et al., 2009). Combining these data-collection approaches with LCMs has the potential to improve both availability of microdata and the degree to which findings from LCM projects make their way to a diversity of participants in the land system.

High-Performance Computing

A second opportunity for which cyberinfrastructure developments show promise is the increasing ability to meet the computational demands of some of the modeling approaches outlined above. Given increasing data volumes and model interactions that might be expected for some modeling applications based on the opportunities outlined above, developments in processors, data storage, and network bandwidth all offer important improvements. For example, coupling land change and environmental process models at high resolutions provides opportunities to explicitly incorporate information on fine-scale patch or parcel adjacency, connectivity, and shape, which regional to global-scale models often leave out or attempt to parameterize as subgrid-scale phenomena. Models that incorporate finer-scale spatial interactions over larger spatial domains would provide benefit to regional and global-scale models. The advent of spatially distributed models in the environmental sciences has both required higher-resolution information to resolve shape, adjacency, or connectivity, and developed a greater demand for this information, including LULC. Distributed data storage, which can be used to maintain archives of large longitudinal data sets, together with increased network speeds facilitates these kinds of model developments and model couplings. These developments will surely require that taking advantage of these opportunities will require new approaches to engineering and implementing LCMs. In another example, the integration of optimization approaches into land change modeling to represent agent decision making and to develop optimal land patterns and functions, particularly at finer resolutions and over heterogeneous areas, requires use of both advanced computational tools and new heuristic approaches to improve their computational feasibility (Batty, 2008; Wright and Wang, 2011).

Advances in processing power are increasingly based on deployment of multiple processing cores and increasing numbers of processors. Distributed computing takes advantage of processors that are linked across networks and present opportunities for distributing modeling and simulation tasks. New architectures like graphic processing units (GPUs) also offer enhanced capacity. Taking advantage of this enhanced computing power requires that models be written to take advantage of parallel processing, that is, the partitioning of computational tasks among multiple processors running simultaneously. When significant data communication is required between parallel processing tasks, the advantages of parallel processing can be reduced and careful design of the parallel algorithm is required. For this reason, some modeling approaches and problems will be able to benefit from these developments in computing more than others. Li et al. (2012) report a 30-fold increase in processing speed for a cellular automaton model running on a GPU versus a traditionally developed model. Tang and Bennett (2011) were also able to achieve between 10 and 40 times the processing speed by running an agent-based model of opinion diffusion on a GPU.

OPPORTUNITIES FOR INFRASTRUCTURE TO SUPPORT LAND CHANGE MODELING

Progress in land change modeling is partially impeded by the continued reinvention of modeling environments, frameworks, and platforms by various research groups. Below are some specific findings regarding research infrastructure that could facilitate solutions to overcome this barrier. Specifically, we identify three kinds of infrastructure investments that would facilitate integration, comparison, and synergy across the community of land change modelers: model infrastructure, data infrastructure, and community governance.

The community infrastructure envisioned for land change modeling might be modeled on existing structures developed within other fields. For example, the atmospheric modeling community has developed a community infrastructure for building, providing data inputs to, comparing, validating, and learning from atmospheric and related models aimed at global change science. This has evolved as the Community Earth System Modeling community, and it includes a number of working groups focused on specific aspects of the Earth system (http://www.cesm.ucar.edu/). One working group, focused on the "Community Land Model," is developing modeling capabilities that focus on "ecological climatology" in order to better link physical, chemical, and biological aspects of the land surface to atmospheric processes (http://www.cgd.ucar.edu/tss/clm/). The effort does not include any of the social and economic processes needed to model land use dynamics, but represents a potential model for infrastructure development and governance for future community efforts in land change modeling. This includes regular open meetings, a community model development approach, model intercomparison activities, and compilation of data sets and activities for model validation. The heterogeneity of approaches to LCM outlined in this report may require a structure that accommodates a wider range of applications. These issues are explored below.

Model and Software Infrastructure

A model infrastructure would address the need for models, model code, and model platforms that can be used to avoid duplication of effort among various constituents in the land change modeling community. Such an infrastructure should be open source to permit contributions from and availability to participants from throughout the scientific community. Some of this infrastructure exists in various forms already, as existing open-source platforms and models. The challenge for the LCM community is assembling this existing infrastructure and building on it in such a way that it can serve as a platform for (a) further advancing fundamental understanding and representation of land change processes and (b) integration with a wide range of biophysical and socioeconomic models for evaluating the impacts of land change.

Existing open-source models have served the community well and have allowed scientists to include land change dynamics in studies across various fields and applications. For example, SLEUTH is a cellular model that has been used extensively in studies of urbanization (Clarke and Gaydos, 1988; Clarke et al., 1997; Herold et al., 2003) and its effects on urban landcape dynamics (Berling-Wolff and Wu, 2004; Syphard et al., 2005) and watershed impacts (Claggett et al., 2004; Jantz et al., 2010). CLUE, also a cellular model, has been used widely to generate land change scenarios and impact assessments at regional scales (Lesschen et al., 2007; Veldkamp and Fresco, 1996; Verburg et al., 2006; Wassenaar et al., 2007). UrbanSIM, a microsimulation model that is similar in character to agent-based models, has been used in a number of cities to develop forecasts of urban development, travel demand, and environmental impacts (Waddell, 2002) and has been used in Seattle (Waddell et al., 2007); Paris (de Palma et al., 2007); Detroit; Durham, North Carolina; Honolulu; and Houston, among others. Use of existing models is attractive at least partially because of the time required to build models. A number of challenges with using existing models include (a) poor understanding on the part of the user of the underlying mechanisms and parameters, (b) related to the first, inappropriate application of a model in situations or at scales for which it is not suited, and (c) difficulties of understanding code structures and details, which can make modifications very time consuming to make. Problems (a) and (c) above are made more acute when models are developed with proprietary processes and codes, because users have a harder time assessing and adapting these models.

To facilitate more expeditious construction of models and greater ease of model modification and integration, a number of open-source modeling environments have been developed that are either intended specifically for land change modeling or more general modeling environments that are suitable for land change modeling applications. In the former category, Dinamica EGO provides an environment for graphical construction of scripts that implement cellular models based on a number of primitive operations, referred to as functors (www.csr.ufmg.br/dinamica/). While the framework has the more general applicability of model builders within GIS packages (like ArcGIS and *Idrisi*), it has been most commonly applied to land change questions (e.g., Soares-Filho et al., 2006, 2010; Thapa and Murayama, 2011). The Open Platform for Urban Simulation (OPUS) was developed by the team that produced UrbanSim as a more general model development environment for building and testing urban models (Waddell et al., 2005; www.urbansim.org/downloads/manual/dev-version/opus-userguide/). OPUS uses Python to access object codes that can be used to build more complex models.

A wide variety of other general modeling environments have been used for building land change models. For agent-based models, the earliest open-source tool was Swarm (www.swarm.org), which required models to be developed in the objective-C language. Repast (repast.sourceforge.net) offers similar software functions to Swarm, but the models can be developed in the more common Java language, C++, or Python. Among many other agent-based modeling platforms are NetLogo (http://ccl.northwestern.edu/netlogo/), in which models are developed within its own high-level programming language, MASON (http://cs.gmu.edu/~eclab/projects/mason/) based on Java, and Cormas (http://cormas.cirad.fr/indexeng.htm) based on Smalltalk. Each of these environments provides software tools that can be incorporated into new agent-based models (in the form of programs) that can be used to represent model components, control model function, and evaluate and visualize model output. Because cells can be treated as agents in these model environments, cellular models can also be implemented using these platforms. The Global Trade and Analysis Project (GTAP) has served as an important platform for developing a variety of computable general equilibrium models, including those related to land use change (www.gtap.agecon.purdue.edu). While the model platform itself is not open source, the GTAP database that is the core of the project has been developed through open-source institutional arrangements. Econometric models are generally developed with software platforms aimed at statistical analysis. R is an important open-source platform for development of statistical models, including econometric models (http://www.r-project.org/). R provides tools for data calculation, statistical estimation, and visualization that are accessed through the R scripting language.

Infrastructure to support future developments in land change modeling will surely need to build on these existing resources, but efforts at coordination toward the needs of land change modeling will be beneficial. Such coordinated efforts should aim toward identifying the various constituent processes of land change and developing software components that represent those constituent processes. Formal descriptions of such components can become an important step toward combining parts of models and developing modules that can be changed or interoperated. For example, Parker et al. (2008) described a “conceptual design pattern” for agent-based models of land use change that serves as an example of the kind of general model descriptive framework that can be envisioned and implemented. This conceptual design pattern describes land change processes in six conceptual design considerations that might define modules of any given land change model: information/data, interfaces to other models, demographics, land use decisions, land exchange, and model operation.

Apart from attempts to develop modules that can interact within a common framework, the development of formal model descriptions can help with communication and replication of existing models or model components. Just as standards for descriptions of data have been critical to the advance of data sharing and interoperability, descriptions of models are equally important, but they are less well developed. A first attempt was made at a metadata content standard for computational models (Smith et al., 2001), but this standard has not been further developed. The Overview, Design concepts and Details protocol was proposed (Grimm et al., 2006) for agent-based models and has been widely used within the community of researchers using these models. However, further development of such standards and protocols within the land change modeling community could help further advances in model development and application.

Data Infrastructure

A data infrastructure would provide access to a common set of data resources that are necessary for running and validating models of land change. The majority of respondents to the committee's user community questionnaire expressed some level of support for such a common set of data resources. The second section of this chapter outlines data sources that are essential to the land change modeling enterprise, from historical data on land use and land cover change at multiple scales to a variety of demographic, economic, and policy inputs to land change models. The challenge of modeling land changes is exacerbated by the diversity of data requirements and the need for these data to be collected over time. Although a variety of data sets exist to support these needs, further developments in improving spatial and temporal resolutions and better representing changes over time would be facilitated by a formal data infrastructure to support land change modeling.

Existing resources include a variety of national and regional agencies supporting data on land cover change, often provided by space agencies as products from satellite image programs. For example, the National Aeronautics and Space Administration (NASA) supports the "Global Land Cover Facility" as a provider of image data and derived land cover products (http://glcf.umiacs.umd.edu/data/). GlobCover is a product provided as a service of the European Space Agency in conjunction with the United Nations Food and Agriculture Organisation (http://due.esrin.esa.int/prjs/prjs68.php). Aside from satellite image data that can be used to collect land cover information consistently over regional to global extents, existing data at subnational and local levels is more heterogeneous and, therefore, difficult to compile in comparable formats. Some efforts have been made to do so for land and demographic data sets. For example, global historical land cover data (1700-2000) have been compiled through a number of research projects that have been aimed primarily at supporting global Earth system dynamics models with dynamic land cover information (Hurtt et al., 2006; Klein Goldewijk and Ramankutty, 2004). Furthermore, the Center for International Earth Science Information Network, supported through NASA's Socioeconomic Data and Applications Center, compiles and provides access to a variety of global socioeconomic data that can support land change model development. Compiling comparable data from local-level cadastral, land use, survey, and other data sets is an important challenge for the land change modeling community.

Future infrastructure developments need to further support compilation, curation, and comparison of the heterogeneous data sources for input to, and parameterization and validation of LCMs. This component of the infrastructure for land change modeling requires open access to, documentation of, and structured organization of heterogeneous data for land change science. A couple of existing data infrastructure models are worth exploring, and also connecting to, as they include data to which the land change modeling community might reasonably expect to connect. GEON serves as a set of software and data resources that supports data sharing and integration in the Earth sciences communities and has focused on digital elevation, geophysical, and bore hole and well data (www.geongrid.org). Early stages of this network required development of common semantic frameworks for describing and modeling data with heterogeneous semantic and spatial definitions and scales, and the links between them (e.g., Vaccari et al., 2009). The Consortium of Universities for the Advancement of Hydrologic Science has developed a hydrological information system that links together data on the hydrologic environment (his.cuahsi.org) and was developed through a similar data publishing and integration process (e.g., Horsburgh et al., 2009). Similar to both of these projects, a data infrastructure to support land change modeling would need to recognize the different thematic data that are necessary; recognize their heterogeneous semantic, spatial, and temporal referencing; and develop a structured system for access and integration in the form of a global integrated land information system.

A number of promising developments in this direction might be helpful to the development of such an integrated system. Examples include, first, the recent support by the National Science Foundation for the Global Collaboration Engine, which aims to facilitate integration of data and models working at various scales specifically for the land change modeling community (ecotope.org/projects/globe). The project aims to provide global data that can be used to enhance comparability among diverse case studies, which are a common mode of data analysis within land change science. Second, the TerraPopulus project aims to integrate data on population, land cover, climate, and land use across the globe and over time. The population data include commonly used aggregated microdata on individuals, which are compiled as part of the IPUMS-International project (www.terrapop.org). Finally, the Geoshare project (https://geoshareproject.org/) aims to coordinate global data relevant to economic analysis of global agriculture and land use systems. Each of these projects is still new at the time of this writing, so how they develop to support land change modeling has yet to be proven.

Community Modeling and Governance

A community modeling and governance infrastructure that supports developments in land change modeling would provide mechanisms for decision making and advancement of modeling capabilities within a broad community and toward specific, achievable goals and capabilities. A community of land change modelers could settle on a series of specific goals and endpoints and work together with input from that broad community to move modeling and data capabilities forward in ways similar to those outlined in the previous two sections. The majority of respondents to the committee's informal user community questionnaire either supported or saw value in such community models.

Two existing structures serve as potential models for how such a community structure might work. The first is that used for the Community Earth System Model (CESM), which currently has a sub-component called the Community Land Model, described above. This model effort is carried out by a group of researchers who seek funding on their own to provide advancements within a democratically governed framework, organized by working groups, to make changes to the model. All changes must be freely available with open code and documentation, which is the responsibility of the developer. For example, a new working group on a community land use model could decide to further develop the details of the conceptual design pattern outlined by Parker et al. (2008), or some other framework, that can then serve as a basis for development of plug-and-play land change modules that could be used to construct a variety of different land change models that are linked to a variety of other environmental models. The newly formed Societal Dimensions Working Group with the CESM framework could be an institutional location for the work, or some subset of it.

A second structure is that offered to the community of modelers applying agent-based modeling to understand socioecological systems in the form of the Network for Computation Modeling for SocioEcological Science, which maintains openabm.org as a platform for sharing open models and resources and is working on developing and furthering protocols for model documentation and development. A much looser confederation of modelers, this structure provides a rule-based framework within which modelers can contribute a wide range of models and around which specific outcomes or goals do not need to be agreed upon.

MODEL EVALUATION

There are a variety of practices that can enhance land change modeling to make it more scientifically rigorous and useful in application. Some of these practices are established but not always followed, whereas others require more research to test and establish. A set of reviews and standards have been produced of best practices for environmental modeling (e.g., Crout et al., 2008; EPA, 2009). Here we summarize best practices in the evaluation of LCMs in four broad categories: sources of uncertainty, sensitivity analysis, pattern validation, and structural validation.

Sources of Uncertainty

Uncertainty in LCMs can come from a variety of different sources. The data concerning inputs and values of model parameters usually have some level of error. These data describe the boundary conditions (e.g., initial land cover) and exogenous dynamics (e.g., price fluctuations). Additionally, the model structure itself will have some uncertainty associated with it, including the processes represented in the model, their interactions, and how they are represented mathematically or algorithmically. The uncertainty in these aspects of the model can stem from both incomplete information about their historical states, due to uncertainties or unavailability of data, and variations in their states over some observation period (i.e., nonstationarity in the process). Substantial uncertainty in forecasting future states is often due to nonstationarity in processes. Nonstationarity may exist due to changes in exogenous conditions that cannot be endogenized within the model, and shifts in processes that are poorly understood (e.g., changes in human decision making due to developing cultural attitudes or preferences). Although quantification of model uncertainties provides important evidence about model efficacy, these uncertainties must be placed in the context of an understanding of the effects of nonstationarity in the process on the predictive ability of any given model.

There are as many possible measures of stationarity as there are measures of change. A process might be stationary according to one measurement but not according to another measurement. It is essential to understand whether a process is stationary according to particular measurements when LCMs are used to extrapolate historic trends. It is possible that the land change process during the historic calibration interval is different than a more recent time interval that is used for validation in terms of the structure of the process or the magnitude of various drivers. If this is the case, an extrapolation model will not have a high measurement of validity. Thus, it is necessary to understand the stationarity in the process before engaging deeply in empirical-based modeling. Many modeling exercises begin by creating a business-as-usual scenario, which is a scenario that extrapolates historic trends. However, if historic trends have been nonstationary, then historic business has not been usual, in which case it makes little sense to construct a business-as-usual scenario.

Sensitivity Analysis

Sensitivity analysis is an established procedure whereby the investigator examines the variation in model output due to specific amounts of variation in model input, parameter values, or structure. Sensitivity analysis can be useful to evaluate the importance of uncertainty arising from multiple sources and to understand better the situations in which the modeled system may show important changes in behavior. Evaluation of the sensitivity of a model to one or more parameters can be evaluated by perturbing a parameter's value over a specific range, thus creating a range of outputs. The rate of change of results relative to inputs provides an assessment of sensitivity. Sensitivity will vary both by parameter and by the initial value of the parameter that is perturbed, such that sensitivity may be a local property. Extension to two or more parameters is accomplished in a similar manner, by simultaneously perturbing multiple parameters, and facilitates evaluation of interaction effects of the parameters (Ligmann-Zielinska and Jankowski, 2008).

A similar approach can be accomplished by perturbing values of one or more data inputs to establish sensitivity of the model to the range of exogenous forcing information, or to initial conditions. Additionally, sensitivity analysis can be applied to model structure, both for cases where separate models will be evaluated and where there are options for different process representations in the same model. Because differences in structural or dynamic characteristics of a model are important elements of sensitivity, comparison of single-map outputs may be inadequate for evaluating model sensitivity, and evaluations may need to be made over the entire course of a model run (Ligmann-Zielinska and Sun, 2010) or in ways that compare across multiple runs of the same model (Brown et al., 2005).

It is important to perform sensitivity analysis in a manner that relates to the particular research question because models can make many minor or self-cancelling errors that are ultimately not important for a model's particular purpose. For example, in a model whose purpose is to simulate carbon dioxide emissions as a result of deforestation, errors of omission in predicting land change that balance with errors of commission can be ignored as not important in terms of the goal of estimating total carbon emissions. In one study, a comparison of seven different carbon maps indicated that uncertainty in the quantity of carbon is much more important than uncertainty in how the land change model simulates the spatial allocation of deforestation (Gutierrez-Velez and Pontius, 2012).

Model selection sometimes makes a large difference in results, but sometimes model selection is not the most important factor. For example, a comparison of the predictive accuracy of the output maps from two models, cellular automata/Markov versus Geomod, found that the variation in results between models was less than the variation within a model due to parameter selection.

Best-practice modeling should result in models with a level of complexity no greater than what is required for a specific project or application. Models that have too many parameters and assumptions are difficult to calibrate and validate. Sensitivity analysis offers one method to prioritize research and determine the most important parts of the model to develop. If the results of a LCM are insensitive to certain processes or parameters, then the model or efforts to determine parameter values can be simplified. This allows prioritization of effort and resources toward more sensitive processes, parameters, and input data. Thus, sensitivity analysis can facilitate the design of research to simplify the model and to focus effort on the most sensitive parts of a model.

Pattern Validation

Evaluation of model performance often requires comparison of model simulations with observed outcomes. Simulations from LCMs usually produce maps of land use, land cover, or some other land-related variable. A standard approach to evaluating the simulation of a land change model is to develop the model through calibration with historical data, for example using two or more maps of land cover during the calibration time interval. The calibrated model then simulates a validation to another time point for which reference data are available. The map of simulated change is then compared with the map of actual reference change during the validation interval to evaluate the differences based on some set of metrics. This comparison requires three maps: the reference map at the start time of the simulation, the reference map at the end time of the simulation, and the simulation map at the end time of the simulation. This three-map analysis shows how the simulated change compares to the reference change by revealing five components: (1) reference change simulated correctly as change (i.e., hits), (2) reference change simulated incorrectly as persistence (i.e., misses), (3) reference persistence simulated incorrectly as change (i.e., false alarms), (4) reference persistence simulated correctly as persistence (i.e., correct rejections), and (5) reference change simulated incorrectly as change to the wrong gaining category (i.e., wrong hits) (Pontius et al., 2011). The relative value of each of these five components can be used to compute quantity disagreement and allocation disagreement (Pontius and Millones, 2011).

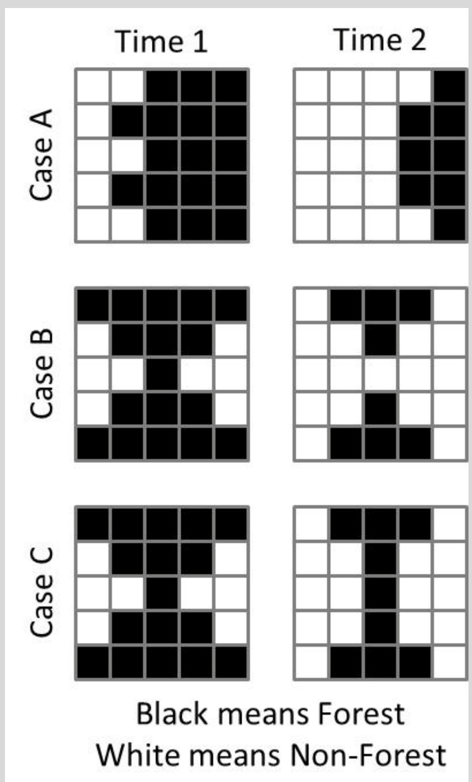
The three-map comparison and its five components reveal the accuracy of the land change model versus a null model that predicts complete persistence. Where the land change model generates a miss, the null model would also produce a miss. Where the land change model generates a false alarm, the null model would produce a correct rejection. Where the land change model obtains a hit or a wrong hit, the null model would produce a miss. Thus, if the modeler computes the five components of the three-map comparison, the modeler has produced a comparison with a null model. A frequent blunder is to compute a two-map comparison between the reference map at the end time of the simulation and the simulation map at the end time of the simulation. This two-map comparison cannot distinguish between correctly simulated change (i.e., hits) and correctly simulated persistence (i.e., correct rejections).

After the modeler sees the map of the five components, there are a variety of more detailed ways that the modeler can compare the pattern of simulated change versus the pattern of reference change. There are a plethora of pattern metrics that consider the spatial distribution of the patches in the map. Such metrics can consider the patches' numbers, sizes, and shapes. The particular research question should dictate whether details concerning the configuration of the patches in the map are important. For example, if the application concerns biodiversity protection, then it is likely to be important to consider whether forest is in one large patch or several smaller patches. If the goal is to measure the quantity of carbon emission, then the configuration of the patches is probably less important. It can be tricky to select a metric that is mathematically rigorous, intellectually assessable, intuitively interpretable, and practically useful (see Box 3.1). A necessary best practice is to match the measurement of the model with the purpose of the modeling exercise for the particular application. This is an area that requires more research.

Whatever metrics the modeler adopts, it is important to use the metrics to compare the output from a land change model to the output from a corresponding naïve model that is applied to the same study site. A naïve model is one that is based on a simplistic conceptualization of the land change process and that offers a baseline that is easy to understand and implement. For example, a naïve model of deforestation could allocate the simulated deforestation on the edges of the initial forest patches. Then the output from the naïve simulation could be compared to the output from a more complex model. It is important to compare the output from a complex model to the output from a naïve model to measure whether there is any increase in predictive ability in the more complex model. A naïve model might use randomness to allocate change, but researchers frequently already know that the process of change is not random; thus, a random

Box 3.1
The Challenge of Selecting a Pattern Metric

Selecting an appropriate pattern metric that can indicate process is a challenge. Many modelers are interested in measuring the output of maps based on the spatial pattern metrics of the maps, such as number of patches. The figure below contrasts three cases where we compare the land change between two time points. All three cases have one patch of forest at time 1 and demonstrate a process where deforestation occurs on the edge between forest and nonforest. However, this single process generates different patterns due to interaction between various initial configurations and quantities of change. In this example, case A has a different initial configuration than cases B and C, while case C has less deforestation than cases A and B. Cases A and C have one forest patch at time 2, while case B has two forest patches. This illustrates how the number of patches can be sensitive to an interaction between the configuration of the initial landscape and the quantity of change.



model is likely to produce an extremely low baseline. A naïve model that is based on one simple idea such as proximity to a single feature is likely to generate a much more challenging baseline than randomness. For this reason, it can be misleading to use metrics, such as kappa, that compare model output to a random pattern (Pontius and Millones, 2011). The literature sometimes uses the term *neutral model* to convey the idea of a naïve model that offers a baseline for comparison to a more complex model; however, if neutral models are based on randomness, then such neutral models are likely to produce an unchallenging baseline.

If there is no baseline for comparison, then the investigator is frequently tempted to use universal standards for model performance, such as defining good as greater than eighty-five percent agreement between the simulated map and the reference map. Universal standards for model performance are problematic, because they are by definition not specific to any particular research question or study site.

The concepts of equifinality and multifinality also need to be considered when selecting a metric for model assessment, especially when that metric measures only the pattern in the output map (Brown et al., 2006). Equifinality is the situation where two different processes produce the same result. For example, uniform versus highly variable patterns of risk aversion might, in some settings, produce identical patterns of agricultural activity. In this situation, it is possible that the model uses an incorrect process to produce the correct pattern.

In other cases, a process-based model uses the correct process to generate an incorrect pattern. Multifinality is the situation where a single process has the ability to generate many different patterns. One possible cause for this phenomenon is path dependency, whereby a few initiating events occur due to a poorly understood process, and then those events trigger numerous other processes. For example, there might be tremendous uncertainty where a corporation will build a facility, but then the facility generates urban growth near wherever it is placed. Thus, a model can simulate correctly the process of growth that follows the initial siting of the facility, but the model realizes that there is uncertainty in the placement of the initial facility. In this situation, a process-based model simulates the correct process, but it might not produce the correct pattern, as measured by a particular pattern metric.

Structural Validation

Models may have predictive accuracy in the sense that they generate predicted land use patterns that exhibit a close correspondence to the actual land use pattern at some point in time. Models can also have process accuracy, which Brown et al. (2005) define as consistency between real-world processes and the processes by which locations or land use patterns are determined in the model. Devising ways of validating model processes remains a challenging task in part because the underlying processes that give rise to observed land use patterns are themselves not fully observable. In addition, because more than one process may generate a qualitatively similar land use pattern, there is not a one-to-one mapping between the hypothesized underlying process and the predicted pattern. Finally, interactions and other sources of nonlinearity imply that many processes related to land changes may be path dependent, in which case small random or poorly understood shocks in the process may cause large deviations in observable land use–pattern outcomes. The implication is that the underlying process cannot be discerned based on the observed patterns and additional information is needed to identify the underlying process (Epstein, 2006).

Process validation may occur at several different levels of modeling. In the simplest case, the focus may be on identification of one or more key structural parameters of the process. Data over time can be extremely useful in addressing this challenge. Panel data techniques commonly used in econometrics permit the researcher to control for unobserved spatial heterogeneity, for example, by controlling for all spatial dependence so that a causal effect can be identified. Robustness checks are a common means of validation, for example, by using an alternative identification strategy or a falsification test that can discern spurious effects of the data.

Grimm et al. (2005) offer an approach to process validation that makes use of comparisons of observed and predicted patterns, like those outlined in the previous section. However, in their *pattern-oriented modeling* approach, the emphasis is on identifying multiple dimensions of pattern that may be very different from one another in character. For example, depending on the goals of the model, the different patterns produced by an agent-based model that could be compared with data, could include maps of land cover, distributions of income, rates of deforestation over time, and numbers of actors engaged in off-farm income. The patterns are classified as primary patterns (i.e., those that the model was built to explain) and secondary patterns (i.e., those that the model can generate but are secondary to its primary purpose). The argument is that the more patterns a model can reproduce, and the more disparate those patterns are in character, the more likely we are to be able to validate the mechanisms by which the model produces those patterns. This is an indirect approach, but offers promise for structural models (like agent-based models) that can produce various types of outcomes.

More challenging is validating the assumptions that are necessary to specify a model. For example, models of land development or household locational choice are based on maintained assumptions regarding the structure of producers' costs or households' preferences from which the specific functional form of the model is derived. Validating these assumptions requires collecting additional information, devising strategies to test these maintained assumptions, and quantifying the degree of uncertainty surrounding these assumptions given that they are sometimes unverifiable. Kuminoff (2009) provides an example of how the maintained assumptions of functional form, preference distributions, and neighborhood delineation (all used in structural econometric models of household locational choice) can be assessed in terms of their influence on model results. This approach provides a means for quantifying how uncertainty regarding the maintained assumptions of the model impacts the model's predictions by clarifying how each assumption influences the model results. Brown et al. (2005) proposed a strategy for quantifying the degree of spatial uncertainty that arises when processes are path dependent, which limits the model's predictive accuracy. They concluded that it is possible to determine an appropriate level of path dependence or stochasticity in the model by comparing results from one model across a wide range of models and landscape patterns. More work along these lines is needed to validate process-based models and to evaluate the reliability of a model's predictions, which is particularly important for guiding policy. This need applies equally to structural and reduced-form economic models as well as agent-based models that rely on a number of maintained assumptions about the agent bidding and market-interactions processes.

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APPENDIX A

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APPENDIX B

Online Questionnaire

The questionnaire below was developed and used by the committee to gather information from key individuals and organizations involved in spatial data infrastructure development and implementation. A total of 116 respondents, 24 percent of whom were from outside the United States, submitted their answers to these questions using an online form.

Online Questionnaire: Land Change Modeling

At the request of the U.S. Geological Survey and National Aeronautics and Space Administration, the National Research Council is conducting a study to review the present status of spatially explicit land change modeling approaches and describe future data and research needs so that model outputs can better assist the science, policy, and decision-support communities. For a full statement of the committee's task, click here.

Because the committee cannot hear from all the individuals and organizations that have valuable experience and ideas on this topic, the committee seeks your help on the following five questions.

Within the context of land modeling:

1. What data products are you using for building, validating, and running land change models?
2. What data products do you most need that do not exist or are not accessible?
3. How might a national sample of land use, land cover, and related data be useful to your work?
4. Would you participate in a land data clearinghouse?
5. Would you participate in a community effort aimed at coordinating development and application of land change models?

APPENDIX C

Committee and Staff Biographies

Committee Members

DANIEL G. BROWN (Chair) is a professor in the School of Natural Resources and Environment at the University of Michigan. His research focuses on land use and land cover dynamics and makes use of multiple methods, including geographic information systems (GIS), remote sensing, digital terrain analysis, ecological mapping, social surveys and statistics, and computer simulation. Specific projects focus on the interacting social and ecological aspects of land use and cover change in rural and periurban environments, land use in climate vulnerability and adaptation, and spatial and social effects on health. He is a fellow of the American Association for the Advancement of Science, and member of the Association of American Geographers, the American Society for Photogrammetry and Remote Sensing, and the International Association for Landscape Ecology. He has written numerous peer-reviewed articles and books. Dr. Brown is also a current recipient of grants from the National Science Foundation and NASA. He is the chair of the U.S. Carbon Cycle Scientific Steering Group and on the board of the Community Systems Foundation. Dr. Brown has served as a member of the National Research Council on the Panel on Human Health and Security and the Space Studies Board. Dr. Brown received a B.A. in geoenvironmental studies from Shippensburg University and an M.A. and Ph.D. in geography from the University of North Carolina at Chapel Hill.

LAWRENCE E. BAND is a Voit Gilmore Distinguished Professor in the School of Geography and the Director of the Institute for the Environment at the University of North Carolina at Chapel Hill. His research primarily focuses on the structure, function, and dynamics of watersheds with an emphasis on the quantity and quality of surface water, and ecosystem cycling of carbon and nutrients. Dr. Band is currently working in a range of watersheds within forested, agricultural, and urban environments encompassing a set of Long-Term Ecological Research (LTER) sites (Baltimore Ecosystem Study and Coweeta), as well as other watersheds in North Carolina. He is a member of the Association of American Geographers, the American Geophysical Union, and the American Association for the Advancement of Science. He has received numerous grants from the National Science Foundation, the Water Resources Research Institute of North Carolina, the Duke Energy Foundation, the Environmental Protection Agency, and the U.S. Forest Service. He has published numerous articles and technical reports. Dr. Band received a B.A. in geography from State University of New York at Buffalo and an M.A. and Ph.D. in geography from University of California at Los Angeles.

KATHLEEN GREEN is the president of Kass Green and Associates, where she consults on geospatial strategy, technology, and policy issues to private, educational, and public organizations and the past President of the American Society for Photogrammetry and Remote Sensing (ASPRS). Ms. Green is former president of both Space Imaging Solutions and Pacific Meridian Resources, a geospatial services company she cofounded in 1988 and sold to Space Imaging in 2000. Ms. Green has given several hundred research presentations throughout the world at various conferences and has published articles in numerous journals. Her scientific service includes current membership on the National Geospatial Advisory Committee, past membership on three National Research Council panels for the National Academy of Sciences, authorship of several chapters of books, and coauthoring the textbook *Assessing the Accuracy of Remotely Sensed Data*. She is a 2011 ASPRS Fellow Award winner. Ms. Green received her B.S. degree in forestry from the University of California at Berkeley, her M.S. degree in resource policy and management from the University of Michigan, and advanced to Ph.D. candidacy at the University of California at Berkeley.

ELENA G. IRWIN is a professor in the Department of Agricultural, Environmental, and Development Economics at Ohio State University. Her research interests focus on land use economics and policy, urban spatial structure, and coupled human-natural systems. Her work includes the development of econometric and simulation-based spatial models of urbanization to examine the influence of policies on urbanization patterns and impacts on ecosystem services. Other work includes the integration of urban and agricultural land use models with hydrodynamic watershed models to study the impacts of landowner and household decision making on water quality outcomes. She has published numerous peer-reviewed articles in a variety of disciplinary and interdisciplinary journals, including Proceedings of the National Academy of Sciences (PNAS), Journal of Environmental Economics and Management, Journal of Economic Geography, Annual Review of Resource Economics, and the Journal of Regional Science. She is the 2008 recipient of the North American Regional Science Council's Hewings Award for distinguished young scholars in regional science and co-recipient of the 2009 Sustainability Science Award from the Ecological Society of America. She received a B.A. from Washington University in St. Louis in German and History (1988) and a Ph.D. in Agricultural and Resource Economics from the University of Maryland (1998).

ERIC F. LAMBIN (NAS) is a professor in the Department of Geography at the University of Louvain, Belgium, and the George and Setsuko Ishiyama Provostial Professorship at the Schools of Earth Sciences and Woods Institute for the Environment at Stanford University. Dr. Lambin has been a leader in the international development of land change science. He has developed novel methods to detect land change at subcontinental and high-temporal resolutions, demonstrated the causal dynamics for tropical deforestation and desertification, and explicated the conditions for transitioning to sustainable land uses. He leads a research team that is involved in several international scientific projects on human-environment interactions in different parts of the world. These projects combine remote sensing, socioeconomic data, and spatial models to better understand and predict terrestrial ecosystem dynamics and their impacts. Dr. Lambin was the Chair of the international scientific project Land Use and Land Cover Change (IHDP/IGBP) from 1999 to 2005. He also contributed to the United Nations program Millennium Ecosystem Assessment. He is consulted by international organizations on issues related to tropical deforestation, desertification, the potential role of tropical forests in mitigating climate change, and environmental impacts of biofuels. Dr. Lambin was awarded the 2009 Francqui prize, the most prestigious scientific prize in Belgium, and has published numerous scientific papers and two broad audience books. He is a member of the National Academy of Sciences. Dr. Lambin received an M.S. and Ph.D. in geography from the University of Louvain, Belgium.

ATUL JAIN is a professor in the Department of Atmospheric Sciences at the University of Illinois. Dr. Jain's research focuses on understanding how interactions among the climate system alter the carbon cycle, and providing useful projections of future changes in global carbon and resultant future climate change. His research goal is to provide the required scientific understanding about how the components of Earth's climate system interact; it is motivated by the practical and pressing issue of human-induced climate change. Dr. Jain has won numerous awards and honors, including the National Science Foundation's Faculty Early Career Development Award. He has served as a lead and contributing author for major assessments of the Intergovernmental Panel on Climate Change (IPCC). He is the author of over 100 scientific articles, including highly cited articles in *Nature* and *Science*, most relating to global climate change as affected by both human activities and natural phenomena. He also directs a number of research projects primarily oriented toward improving our understanding of the impacts that man-made and natural trace gases may be having on the Earth's climate. Dr. Jain received a Ph.D. in atmospheric sciences from the Indian Institute of Technology.

ROBERT G. PONTIUS, JR., is a professor in the Graduate School of Geography at Clark University, where he has advised over 100 theses since 1998. His research and publications focus on geographic information science, land change science, spatial statistics, ecological modeling, and coupled human & natural systems. Dr. Pontius has authored more than 50 peer-reviewed journal articles, has reviewed papers for more than 80 different journals, and is on the editorial board of 10 journals. Most of his grants derive from the US National Science Foundation's Long Term Ecological Research network, which won the American Institute of Biological Sciences Distinguished Scientist Award. Dr. Pontius earned a Bachelors of Science in Mathematics from University of Pittsburgh, a Masters of Applied Statistics from The Ohio State University, and a Doctorate in Environmental Science from the State University of New York.

PETER H. VERBURG is a Professor of Environmental Spatial Analysis and head of the Department of Spatial Analysis and Decision Support at the Institute for Environmental Studies at VU University Amsterdam, the Netherlands. He specializes in spatial analysis and simulation of human-environment interactions, with emphasis on land use and land cover change, ecosystem services, and scenario studies. Dr. Verburg is the developer of the CLUE model (the Conversion of Land Use and its Effects), which is currently used by more than 100 institutions worldwide for simulation for land use change scenarios and ex ante assessment of land use related policies. He chair of the scientific steering committee of the Global Land Project of International Human Dimensions Program on Global Environmental Change (IHDP) and the International Geosphere-Biosphere Programme (IGBP) and will lead the transition of this project into the new 'Future Earth' initiative. Dr. Verburg is involved in a wide range of research projects varying from local scale studies of land use decision making, regional scale spatial modeling, multi-agent systems and ecosystem service mapping to the development of novel global-scale land system change models. In 2012 Dr. Verburg was awarded an ERC independent researcher grant by the European Union. Dr. Verburg received both an M.S. in physical geography and a Ph.D. in land use modeling from Wageningen University, the Netherlands.

KAREN C. SETO is a professor of Geography and Urbanization at the School of Forestry and Environmental Studies at Yale University. Her research focuses on the human transformation of land and the links between urbanization, global change, and sustainability. She specializes in understanding urbanization dynamics, forecasting urban growth, and examining the environmental consequences of land-use change and urban expansion. She is an expert in satellite remote sensing analysis and has pioneered methods to reconstruct historical land-use and to develop empirical models to explain and forecast the expansion of urban areas. Her geographic regions of specialization are China and India, where she has conducted urbanization research for more than fifteen years. Dr. Seto is Coordinating Lead Author for the IPCC Fifth Assessment Report, Coordinating Lead Author for the Cities and Biodiversity Outlook of the UN Convention on Biodiversity, and Co-Chair of the IHDP Urbanization and Global Environmental Change Project. She is also a member of the U.S. National Research Council (NRC) Committee to Advise the U.S. Global Change Research Program, the NRC Geographical Sciences Committee, and the U.S. Carbon Cycle Scientific Steering Group. Professor Seto is a recipient of a NASA New Investigator Program Award, a NSF CAREER Award, and a National Geographic Research Grant. She was named an Aldo Leopold Leadership Fellow in 2009. Dr. Seto received an M.A. in international relations and resource and environmental management, and a Ph.D. in geography from Boston University.

B. L. TURNER II (NAS) is the Gilbert F. White Professor of Environment and Society in the School of Geographical Sciences and Urban Planning and School of Sustainability at Arizona State University. His research focuses on the study of human-environment relationships, distant past to present. Dr. Turner examines these relationships in the use of land and resources by the ancient Maya civilization in the Yucatán Peninsula region, the intensification of land use among contemporary smallholders in the tropics, land use cover change as part of global environmental change, foremost tropical deforestation, and the consequences of environmental tradeoffs resulting from the configuration of landscapes. He has contributed journal articles to the Science, Proceedings of the National Academy of Sciences (PNAS), Ecological Applications, and many other publications. He is a member of the National Academy of Sciences and the American Academy of Arts and Sciences, and a fellow for the American Association for the Advancement of Science. Dr. Turner has served in several editorial positions, including the Editorial Board for Annals of the Association of American Geographers and Regional Environmental Science, and is an Associate Editor of PNAS. Dr. Turner received B.A. and M.A. degrees in geography from the University of Austin at Texas and a Ph.D. in geography from the University of Wisconsin at Madison.

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NICHOLAS D. ROGERS is a financial and research associate with the Board on Earth Sciences and Resources, National Research Council. He received a B.A. in history, with a focus on the history of science and early American history, from Western Connecticut State University in 2004. He began working for the National Academies in 2006 and supports the Board on Earth Sciences and Resources on a wide range of areas from earth resources to geographical and mapping sciences.

JASON R. ORTEGO was a research associate with the Board on Earth Sciences and Resources at the National Academies until July of 2012 and is currently a Program Officer with the University of California. He received a B.A. in English from Louisiana State University in 2004 and an M.A. in international affairs from George Washington University in 2008. He began working for the National Academies in 2008 with the Board on Energy and Environmental Systems, and in 2009 he joined the Board on Earth Sciences and Resources.

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