LAND USE AND THE CARBON CYCLE

Advances in Integrated Science, Management, and Policy

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Modeling for Integrating Science and Management

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1. Introduction

The stakeholders involved in management of land and carbon (C) are diverse. Farmers and foresters are concerned with plants and management practices that are most likely to sustain profits. The opportunity to sell C sequestration credits adds a new dimension to production strategies. Land managers may be asking questions, such as how tillage and fertilizer practices in a specific location affect C storage and crop yields. Regional planners and governing bodies may have the opportunity to influence where and how cultivation occurs and interacts with other land uses and industries. They may ask questions related to how crops can be distributed across a landscape to achieve multiple goals that reflect local priorities (water quality, scenic views, traditional lifestyles, tax revenues, etc.). At state and national levels, there are requirements to manage human activities to comply with land, water, and air-emission regulations as well as policy objectives such as job creation and energy security. Decision makers at these levels may desire guidance on how the interactions of policy options provide incentives or disincentives for certain land-use practices and resulting environmental and socioeconomic impacts. Many decision makers are most interested in how scientific information can be used to guide land-use practices in the near term, typically one to five years. However, the scientific information may derive from data measured at entirely different scales or locations and in time spans that range from decades to centuries. With rising attention to global markets and climate change, managers are concerned about how changes in their region are affected by global processes. National and regional decision makers want to know how their choices affect productivity, incomes, C and nutrient cycles, and other development goals. There needs to be a better match between the diverse needs of managers and the information provided by scientific analysis and models.

Models are an important tool in scientific investigations. Britain's Science Council defines *science* to be "the pursuit of knowledge and understanding of the natural and social world following a *systematic methodology based on evidence*."[1] Systems for observing, documenting, and analyzing results are organized under many different disciplines, which share the common thread of being built around observation and measurement. Careful monitoring and measurement leads to new discoveries, new and revised hypotheses, tests of those hypotheses, and, hence, better science. Disciplined measurements that use accepted protocols have much more than a supporting role for science – they form its very foundation. However, for many practical, financial, logistic, and physical reasons, not everything can be observed and measured. For example, some changes occur over decades, centuries, or millennia, and others occur on very large areas, but most measurements record short-term changes in a relatively small area. Support for long-term or large-scale monitoring is scanty and difficult to obtain. Furthermore, the causes and effects of complex relationships are often difficult to discern and change over time, making research results dependent on the temporal and spatial scales of analysis. Therefore, models that are properly designed and used can play a valuable role in elucidating long-term, large-scale, or complex processes. Models are a tool that can be used to explore scientific hypotheses. Ray Orbach likened science to a three-legged stool, the legs of which are theory, experiment, and modeling and simulation (personal communication). All three legs depend on foundations of data.

This chapter describes ways to use models as a bridge between scientific understanding of land-use practices and C flux and the needs of decision makers regarding management of land and C. To do so, we explore the modeling process and types of models that are used for land and C. That topic sets the context for a discussion of the advantages of using models to increase understanding of decision makers about land and C processes as well as cautionary principles. The next section reveals how scientists can best communicate modeling results to decision makers and what decision makers should ask of models. This analysis leads to some recommended practices and a conclusion about the next steps that should be taken to foster improved integration between science and management via models. Because of the diversity of stakeholders involved in these issues, the audience for this chapter is quite broad. Chapter 7 discusses how C is a part of land-use models, and several chapters review and analyze how information related to land use and the C cycle are monitored and measured.

2. The Modeling Process

Modeling is a process that enhances understanding of a system by requiring a formal statement of what is known and not known (Van Winkle and Dale 1998). Modeling is often called an art as there are diverse approaches to capture observed relationships

[1] http://www.sciencecouncil.org/ (accessed July 29, 2012).

using mathematics, and it takes experience, expertise, and creativity to appropriately express complex interactions in what are necessarily simplified constructs. The modeling process requires formulating a hypothesis concerning relationships among components of a system and fosters exploration of the implications of the hypothesis. Thus modeling has an important role in the iterative process of hypothesis formulation and testing (Overton 1977). It influences experimental design, monitoring approaches, and interpretation of results (Van Winkle and Dale 1998).

Models can identify gaps and inconsistencies in knowledge. Aber and Driscoll (1997, p. 647) claim that "models are often more interesting when they fail than when they succeed" because there is more potential for learning when model results are not consistent with empirical observations or current understanding than when results are consistent (e.g., see Lee 1973; Ackerman et al. 1974; Morgan and Henrion 1990; Hall 2000; Meadows, Randers, and Meadows 2004). Inconsistencies inspire scientists to look for other theories and to investigate whether exceptions are occurring. Inconsistency between model output and data can reveal nonstationary processes in the system or poor data quality (Pontius and Petrova 2010; Pontius and Li 2010) even when the model simulates the mechanics accurately. On the other hand, such inconsistency could indicate that a model's underlying assumptions are wrong, the conceptual theory requires revision, key processes are excluded, or combinations of all of the above. If the model instigates in-depth query, then the modeling process has succeeded in fostering enhanced learning. Much can be learned about misunderstandings of system processes responsible for unanticipated outcomes. Initial conclusions from modeling often instigate changes to the original hypothesis or the model itself and thus influence the next step in the scientific investigation.

Models are abstractions meant to represent key elements and interactions of a system so that relationships can be analyzed within established boundaries. Model results are the logical extensions of existing data and are produced via a process that assimilates and applies current understanding. However, models can also mislead and have been used to reinforce common beliefs until a preponderance of evidence supports a better model and eventually overcomes the inertia of long-held assumptions (Box 1979). Box 8.1 describes problems that arise when underlying model theory is not in agreement with empirical data.

Modeling may be used to simulate specific conditions as represented by scenarios of land-use and C cycles in a particular context. Model results can be analyzed to explore potential effects of processes, interactions, or decisions. Models provide a tool for managers to enhance their understanding of the complexities and unique features of a given situation as well as the potential response(s) to management actions or other changes. They also provide a means to project effects under various scenarios and to evaluate possible future outcomes of decisions. Models should be used to test and improve understanding of underlying relationships. However, as the context for modeling expands in spatial and temporal extent, the complexity and uncertainty of both the model and observations increase, making it difficult to test theorized relationships with data.

The modeling process is important to improve knowledge about land use and C. Changes in land cover affect C storage and sequestration processes, but the interactions among changes in C, land cover, land use, management, and long-term storage capacity and productivity are less clear. This disconnect occurs, in part, because scientific knowledge about how to manage for long-term C storage capacity remains limited and, in part, because C has not been a significant goal for managing land. Changes in land use, management, cover, and other land and soil attributes can all affect C storage and fluxes (see Chapters 2 and 3). Although there are detailed, mechanistic models of C flux at the cellular and plant levels, models linking C and land changes at plot scales typically do not incorporate the major driving forces and feedbacks operative at larger scales of land change (Verburg et al. 2004). Another problem in discerning the effects of changes in land and C is selecting the location and temporal and spatial scale of analysis. Land cover and land management are in constant flux, and changes are the product of several major drivers at different scales. The influences of cultural, technological, biophysical, political, economic, and demographic factors on land use are complex, poorly understood, and variable over space and time (Lambin, Geist, and Lepers 2003). There is a great need to sort out the conditions under which certain drivers influence land change and the impact of those interactions (Center for BioEnergy Sustainability [CBES] 2009). No one model represents all of these forces; each approach includes just some of the factors influencing land-use changes.

The ability of a model to integrate scientific understanding in such a way that decision making can be improved depends on the state of the science and data availability, management needs, and conveyance of scientific understanding to managers. The state of the science can range from an explicit, detailed understanding of the key processes with a narrow range of confidence around parameter values to general ideas to be tested, refuted, or incrementally revised with large or unknowable confidence intervals around key variables. Unfortunately, the state of the science supporting the modeling of land use and C cycles varies widely over ecosystems and scales and is often much closer to the "general idea" end of the knowledge spectrum. Although land-use change has been assumed to be a major contributor to greenhouse gas (GHG) emissions (World Resources Institute [WRI] 2009), this assumption and the estimated values associated with it are increasingly questioned (Le Quéré et al. 2009), and land use remains the greatest source of uncertainty in global emission assessments (National Research Council [NRC] 2010) because of the cumulative uncertainty in the types and rates of land-use change, rates of regrowth, and fates of the C involved (Dale and King 1996). Thus modeling should be viewed as part of an iterative process for enhancing scientific understanding, pinpointing needs for better data, and generating better models of land management and C flux to support the decision-making process.

2.1. Key Components of the Modeling Process

The development of a model and the documentation that describes the model and its use should reflect at least nine components. The information that each component requires is summarized in Table 8.1 and described next.

The *purpose* of the model – what processes it was specifically developed to simulate and why – should be clearly articulated. Who developed the model, for what sponsors, and what was the hypothesis that the model was meant to elucidate? The purpose should include a description of the scope of applications that the model was designed to represent.

The *application context* of the model has implications for, sets requirements on, and places limitations on the model and its results. The context includes the phenomenon being modeled, the hypothesis under investigation, the values and interests of the stakeholders, the availability of data, the availability of human and economic resources, the temporal and spatial constraints, the ecological condition of the landscape and its topology, the historic dynamics and rates of change in land cover and its topology, and the needs of the decision makers. Having a conceptual framework for the model as applied to each situation will help to set the context and identify the boundaries to the problem space.

Model *assumptions* depend largely on the model purpose and structure but derive partly from the context. Model results should be interpreted carefully and within the context of the assumptions on which the model is based. These assumed conditions define the time frame and spatial boundaries of concern, processes being modeled, the validity of parameter values, boundary conditions, the completeness and validity of the theory underlying the model, and feedbacks to be included. It is also important to consider what processes and conditions are *not* included. Because these assumptions are typically specific to each situation, caution must be used in applying a model developed for one circumstance to another case. Model assumptions should accurately reflect and reveal the relationships between drivers and effects in the models and the degree to which these relations are based on empirical evidence. For example, some public policies related to the estimated land-use change effects of bioenergy have relied on economic modeling assumptions that lack empirical support (Kline et al. 2011; Kim and Dale 2011).

Inputs include all data and metadata (data about data) needed to run the model. These data include values of variables, variable names, initial conditions, current rates of change, spatial and temporal boundary values, process-specifying control data, data-format information, data tags, and file names and formats.

Table 8.1. *Key components of model documentation*

Component	Description of Information That Needs to Be Provided
Purpose	• Hypothesis • Process or phenomenon being simulated • Applicability
Application context	• Conceptual framework for the model as applied to a specific case • Variables and processes considered exogenous • Reference-case specifications
Assumptions	• Temporal and spatial extent of applicability • Spatial and temporal resolution of each data set and submodel • Process included and not included and how specified (giving citations for underlying theory or observations) • Feedbacks included and not included and how specified • Scenarios used • Questions being asked
Inputs	• All initial conditions and their units • How the initial-condition data were obtained and their sources • Variability in input data
Outputs	• Variables simulated and their units • How the simulations can be used
Calibration	• Iterative process used to determine the set of parameter values that produces the most appropriate model outcomes given the available information • Data used for calibration
Validation	• Process used to determine the soundness of the conceptual framework • Accuracy of the model outcomes • Methods for judging accuracy • Data used for validation
Sensitivity analysis	• How variation in particular parameters affects model outcomes • Method used to identify the influence on model outcomes of variability in parameter values

Component	Description of Information That Needs to Be Provided
Uncertainty analysis	• Assumptions for which there is a lack of knowledge and for which the facts are not obtainable • Risk of uncertain input data and assumptions • Method used to ascertain the uncertainty in model parameters (e.g., errors in experimental design, lack of key measurements, poor understanding of underlying processes, and presence of confounding factors) • Human actions owing to free will

Outputs include all data and metadata produced by the model, such as dependent-variable values, variable names, format specifications, format types (tables, graphs, etc.), and format specifications. If one model's output is further processed or manipulated based on another model or factors generated by a submodel, these steps should be clearly identified as well.

Calibration is the process of determining the set of parameter values that produces the most appropriate model outcomes given the available information. The calibration methods and their reliability and precision should be specified.

Validation is the process of determining the soundness and accuracy of the model outcomes. Validation must be performed in a separate step from calibration and use independent data sets. The validation methods and their reliability and precision should be specified. Models need to be validated by comparing projections to current observational data or historical conditions. However, such a comparison is not always done and may be infeasible in some cases. This is the case with many of the models of land changes. Too often they are not validated or even compared to empirical observations (Kline and Dale 2009). See Pontius et al. (2008) for examples of useful validations. Without proper validation, a model's projections are merely the result of assumptions and initial conditions and should be considered with caution and appropriate skepticism.

Sensitivity analysis of models is a method to identify the influence on model outcomes of variability in the values of specific parameters. Such an analysis typically runs iterations of the model with different values of one input variable so that the variability of the results indicates the sensitivity of the model to that variable.

Uncertainty analysis consists of determining what information is omitted, poorly known, or unknowable and how this absence could affect modeling results. The strength and validity of a theory to describe a given phenomenon may be a source of uncertainty (however, Box 8.1 describes a situation in which an invalid underlying theory led to repeated efforts to increase precision and reduce uncertainties within the model rather than revise the underlying theory). Some uncertainties are irreducible, and some may not be bounded by probability, but these can be critical for understanding total uncertainty (Tannert, Elvers, and Jandrig 2007). Uncertainty analysis complements sensitivity analysis by helping a user identify the limits of the model's applicability.

Box 8.1

An Example of Problems That Arise When Underlying Model Theory Is Not in Agreement with Empirical Data and Their Implications

The Copernican Revolution in astronomy provides an example of how setting forth the underlying theory of mathematical models is essential to documenting how models are used to explain observations. In 1543, Copernicus published a mathematical model explaining the theory of a heliocentric planetary system, which displaced the Earth from the center of the universe. However, it was not until 1822 that the model was formally accepted by decision makers in the Catholic Church and much of the general public. In the intervening centuries, earlier mathematical models were repeatedly adjusted so that they could better explain the observed phenomena without changing the assumption that Earth was at the center of the solar system. In particular, the Ptolemaic (or geocentric) system was repeatedly revised to explain observed movements of the planets. The adjustment of the Ptolemaic model was necessary to support a simple and fundamental conceptual belief – reinforced by apparent observation each day – that the sun circled around the Earth. Meanwhile, scientists such as Kepler contributed further analysis, and Galileo conducted telescopic studies that supported the heliocentic theory and the model of Copernicus. It took a preponderance of evidence and a great deal of time for leaders deeply invested in the geocentric model to accept change.

A similar situation may be occurring as general economic models are applied to support the belief that U.S. ethanol policy causes an increase in global deforestation. The models estimating these indirect land-use changes do not include many of the key underlying social, cultural, political, and ecological processes known to drive deforestation. This is not surprising considering that global economic models were developed for entirely different purposes. Empirical evidence from the first decade of ethanol growth in the United States (2000 to 2010) provided little support for the assumptions and land-use change results produced by the models (Oladosu et al. 2011). Adjustments to the models could make marginal improvements; however, if a model does not incorporate appropriate theory, it is unlikely to adequately explain the observed patterns. Alignment or discrepancy will become more apparent as more accurate observations are accumulated. Regardless, it is not that a model is good or bad (an odd concept in itself) but rather that a model is unlikely to be appropriate for describing changes if known drivers for change are omitted. Therefore, it is critical that underlying theory be set forth as part of the model documentation.

Examples of processes not included in many land-use change models are reversibility and repeated use of fire in the historic baseline. The fact that land is typically cleared and burned to formalize a claim, and reburned repeatedly in the absence of market demand, is not included in current models. Such land is more likely to rebuild C stocks above- and belowground when it is brought into productive management, generating an effect from indirect land-use change that is diametrically opposite of prevailing global equilibrium model estimates (CBES 2009). Furthermore, if reversion occurs within a short time frame, there may be no indirect land-use change effect (net emissions from land-use change would be zero); however, the Environmental Protection Agency's Renewable Fuel Standard specifically omits land reversion (see http://www.epa.gov/OMS/renewablefuels/rfs2-peer-review-emissions.pdf [accessed March 23, 2012]). To improve validity and accuracy, models used to estimate indirect effects of bioenergy should adequately incorporate baseline and ongoing land-use changes as a part of their processes (Kline et al. 2011; Gnansounou et al. 2009; Keeney and Hertel 2009; Kim, Kim, and Dale 2009).

2.2. Types of Models

There are many types of models, including heuristic, physical, and mathematical (Dale and O'Neill 1999). Heuristic models are relatively simple but capture key relationships of the system in a nonquantitative way. They can be depicted as pictures, diagrams, words, or simple mathematical relationships (such as inequalities) rather than accurate, absolute measures. Many conceptual models fall into this category because they provide a simple qualitative and transparent representation of the system being studied. Such approaches are designed to reveal how a system works.

One example of heuristic models is the conceptual approach that has been applied in most economic modeling of land-use change associated with bioenergy policies (Figure 8.1), which begins with two basic land classes: forests and cultivated areas. By starting with this simple model, the effect of an additional demand for land for bioenergy crops inevitably leads to displacement and land-use change. The model does not attempt to ask *if* land-use change occurs; rather, it presumes that land-use change occurs and then estimates *how much* occurs under different scenarios.

An alternative representation of the world would lead to a different modeling approach. For example, the conceptual model developed to portray how land use relates to global economic models in Figure 8.2 (CBES 2009) illustrates the following distinct relationships:

- Initial land-use change is a function of local cultural, technical, biophysical, political, and demographic process
- Subsequent land-use change – what is planted on previously cleared land – is influenced by a distinct set of drivers and is more susceptible to global economic forces

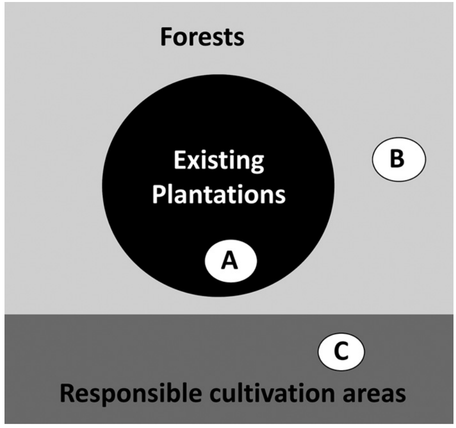

Figure 8.1. A conceptual diagram that is commonly used in economic modeling to project land-use change (adapted from Dehue, Meyer, and van de Staaij 2010). This representation assumes that all land is either in forests or responsible cultivation and has uniform environmental characteristics within a category (such as ability to sequester or release C). The assumption is that indirect land-use change occurs when existing plantations are used to produce biomass feedstock (circle A) and cause expansion of the land use for biomass production to forest or cultivated areas (circles B or C) if there is insufficient reduction in feedstock demand or increase in yield. This conceptual model does not recognize the variability in C sequestration and other environmental variables within each land type or the great availability of previously cleared and underutilized land (Food and Agriculture Organization of the United Nations and International Institute for Applied Systems Analysis [FAO and IAASA 2007]).

The figure points out that there is a difference between land use and the land-cover attributes that are typically used in global economic models. Land use is rarely measured (Dale et al. 2011). As a result, global economic models used to estimate land-use change are based on data sets more reflective of land cover than land use. Furthermore, existing global models typically portray changes in proportions of land cover and only relate to C flux when particular assumptions of current C content are made about the places where land-cover changes occur.

Another example of a heuristic model is a narrative that describes changes in land and C as consequences consistent with the particular scenario depicted (e.g., Richards 1990, Richards and Flint 1994). Such conceptual models are appealing in that they are relatively easy to understand. However, their simplicity may mean that some of the important interactions in the system are not fully characterized.

Physical models are simplified abstractions of the real world, typically constructed in three dimensions. Examples are microcosms, wind tunnels (used to examine aerodynamic properties of airplanes, cars, and seeds), trials and test plots, and aquariums (used in studies of fish population dynamics). Physical models of C flux and land-use change are difficult to construct because of the large spatial and temporal scales involved. As one example, Biosphere 2 is a 1.2 hectare structure built

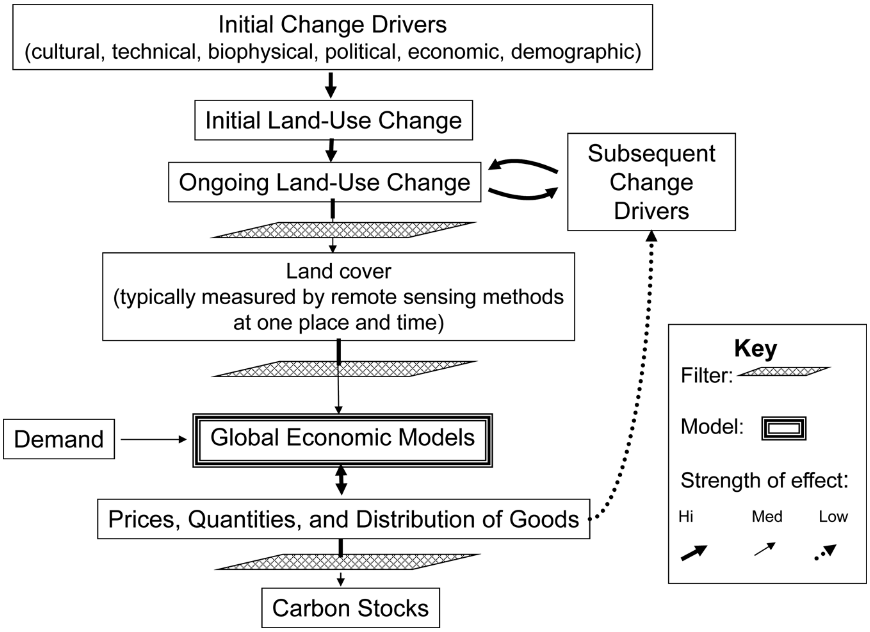

Figure 8.2. Conceptual diagram of the relationships among initial land use, changes in land cover, data interpretation filters, and global economic models, as well as the effects of these components on C flux and subsequent drivers of land-use change [adapted from CBES (2009)].

as a closed ecosystem in Arizona to explore interactions within five biomes and an agricultural area (Allen, Nelson, and Alling 2003). The facility faced major engineering challenges but over two years was able to track great fluctuations in carbon dioxide (CO_2) and declines in oxygen. Biosphere 2 dealt with accelerated rates of biogeochemical cycling and ranges of atmospheric components that occur in closed systems by developing new approaches for air, water, and wastewater recycling and reuse. Much was learned about managing crops using nonchemical pest and disease control. The advantage of physical models is that they provide empirical information and directly relate to the human desire for visualization; however, the Biosphere 2 system is a poor replicate of the Earth. No physical model can capture the full complexity of the interactions between land and C fluxes at global scales.

Mathematical models portray relationships via numeric formulas. Equations are developed to reflect the major processes, interactions, and constraints of the system. This chapter focuses on how mathematical models of land and C can be used to both integrate science and inform decision makers. The many types of mathematical models can be characterized by the approach that is taken to the problem (e.g., optimization), the method used to solve the problem (e.g., analytic versus simulation), or the underlying theory as to which forces are driving change.

There are several approaches used in mathematical models of land change based on different modeling methods and drivers of change (Table 8.2). Transition models assume that the history or scenario is critical to future interactions, whereas agent-based models assume that particular actors (such as land managers and policy makers) are most important to future pathways. Economic models explain land changes as being the result of supply, demand, and relative prices. General equilibrium models represent the whole economy with several interacting markets that seek equilibrium after a simulated shock. In contrast, partial-equilibrium models analyze these forces within a defined subset of the economy. Spatially explicit land-use models account for the role of location in simulating land changes. Biophysical models assume that the physical and environmental settings are prime drivers of change and are sometimes used to project implications of different scenarios (e.g., land management or disturbances). Optimization models employ a problem formulation that sets out to derive conditions under which a specific objective is maximized or minimized given certain constraints. System dynamic models focus on interactions between components of the organization. Table 8.2 and its examples are included to make readers aware of the diversity of approaches and the many models that exist regarding land-use change.

There is often overlap in approaches used to model land changes, typically depending on the questions being addressed and how the models are used. For example, the Integrated Model to Assess the Global Environment (IMAGE[2]) links models within a societal-environmental-climate framework to simulate the consequences of human activities worldwide and to assess sustainability issues related to climate change, biodiversity, and human well-being. As another example, the Policy Analysis System (POLYSYS) (Ugarte and Ray 2000) is a modular partial equilibrium economic modeling system of the U.S. agriculture sector in which planning decisions are made at the Agricultural Statistics District level, and problems about crop demands, livestock issues, and market prices are solved at the national level relative to baseline projections estimated by the Food and Agricultural Policy Research Institute (FAPRI), the U.S. Department of Agriculture, or the Congressional Budget Office.[3]

2.3. Modeling Multiple Drivers

A major challenge in land-use change modeling is considering the implications of different drivers of change. Combinations of models are often used to account for feedbacks and interactions between different sectors. Example model frameworks developed to link the land-use, economic, and energy sectors include economic-biophysical models (LEITAP-IMAGE[4] and GTAP-KLUM[5]), general equilibrium

[2] http://www.mnp.nl/en/themasites/image/index.html (accessed March 23, 2012).
[3] http://www.agpolicy.org/polysys.html (accessed March 23, 2012).
[4] http://ec.europa.eu/agriculture/agrista/2006/scenar2020/final_report/scenar_ch04.pdf (accessed March 23, 2012).
[5] https://www.gtap.agecon.purdue.edu/resources/download/3681.pdf (accessed March 23, 2012).

Table 8.2. *Mathematical models and frameworks used for land-use change (derived and expanded from discussion in Lambin et al. [2003] and Figure 2 in CBES [2009] was provided by L. Panichelli). There is some overlap in the types of models in the table because some applications combine several approaches*

Type of Model and Framework	Key Drivers of Change	Paths toward Stability That Emerge	Examples
Transition model	Scenario or history	Change probability	Mather, Rudel, Moran and Brondizio[a]
Agent-based model	Individual actors, such as land managers	Multiphasic rather than sequential	CASA,[b] Berndes-Sparovek, G4M
General-equilibrium model	Global economic pressures	Equilibrium (by definition)	GTAP, LEITAP, EPPA, DART[c]
Partial-equilibrium model	A specific economic sector (e.g., agricultural economics)	Equilibrium (by definition)	AgLink, ESIM, FAPRI, CAPRI, IMPACT, PEM, POLES, PRIMES[d]
Spatially explicit land-use models	Land suitability, productivity, and available infrastructure and transport costs	Variable	CLUE, KLUM (which uses the Lund-Potsdam-Jena [LPJ] dynamic global vegetation model), GLOB, GEOMOD[e]

[a] Mather and Needle (1998); Mather, Fairbairn, and Needle (1999); Moran and Brondizio (1998), Moran, Brondizio, and McCracken (2002); Rudel, Perez-Lugo, and Zichal (2000).

[b] http://unfccc.int/adaptation/nairobi_work_programme/knowledge_resources_and_publications/items/5323.php (accessed August 14, 2012).

[c] GTAP: https://www.gtap.agecon.purdue.edu/databases/v7/; LEITAP: http://www.mnp.nl/en/themasites/image/model_details/agricultural_economy/Demandforfoodanimalsandcropsproducts.html; EPPA: pdf://rsb.epfl.ch/files/content/sites/rsb2/files/Biofuels/Regional%20Outreaches%20&%20Meetings/LUC%20Workshop%20Sao%20Paulo/background%20papers/RSB-LUC%20-%20Background%20document.pdf and http://globalchange.mit.edu/research/IGSM#EPPA; DART: http://www.cesbio.ups-tlse.fr/us/dart/dart_publications.html (accessed March 21, 2010).

[d] AgLink: http://ageconsearch.umn.edu/bitstream/14808/1/ospawp08.pdf; ESIM: http://wwwuser.gwdg.de/~mbanse/publikationen/dokumentation-esim.pdf; FAPRI: http://www.fapri.iastate.edu/models/; CAPRI: http://www.capri-model.org/dokuwiki/doku.php?id=start; IMPACT: http://www.ifpri.org/book-751/ourwork/program/impact-model; POLES: http://www.enerdata.fr/enerdatauk/tools/Model_POLES.html; PRIMES: http://www.e3mlab.ntua.gr/manuals/PRIMsd.pdf (accessed March 21, 2012).

[e] CLUE: http://www.cluemodel.nl/index.htm; KLUM: http://www.fnu.zmaw.de/fileadmin/fnu-files/publication/working-papers/KLUM_LPJ_WP.pdf; LPJ: http://www.pik-potsdam.de/research/projects/lpjweb; GLOB: http://www.globmodel.info/workshop.html (accessed March 21, 2008); GEOMOD: Hall et al. (1995) and Echeverria et al. (2008).

(*continued*)

Table 8.2 (*continued*)

Type of Model and Framework	Key Drivers of Change	Paths toward Stability That Emerge	Examples
Biophysical models	Biophysical, site-specific issues	Variable	EPIC, DayCent/Century[f]
Optimization models	Maximization or minimization of an objective function, generally economic profit or utility	Equilibrium	GLOBIOM, EUFASOM, FASOM, LUCEA, Panichelli-Gnansounou[g]
Systems dynamics	Organizations, institutions, and their interactions	Dynamic (by definition)	Sheehan-Greene, GLUE, Stamboulis-Papachristos, TIMER[h]

[f] EPIC: http://www.jstor.org/stable/76847; DayCent/Century: http://www.nrel.colostate.edu/projects/irc/public/Documents/Software/Century5/Reference/html/releasenotesv5.htm (accessed March 21, 2010).

[g] GLOBIOM: http://www.iiasa.ac.at/Research/FOR/globiom.html; EUFASOM: http://www.fnu.zmaw.de/fileadmin/fnu-files/publication/working-papers/wp156_eufasom.pdf; FASOM: http://www.fs.fed.us/pnw/pubs/pnw_rp495.pdf (accessed March 21, 2010); LUCEA: Johansson and Azar (2007); Panichelli-Gnansounou: Panichelli and Gnansounou (2008).

[h] Sheehan-Greene: http://www.bio.org/letters/CARB_LCFS_Sheehan_200904.pdf; TIMER: http://www.rivm.nl/bibliotheek/rapporten/461502024.pdf (accessed March 21, 2010).

and partial equilibrium models (GTAP-FAPRI, GTAP-IMPACT, and GTAP-PEM[6]), economic-forestry models (GLOBIOM-G4M[7]), economic-energy models (LEITAP-TIMER[8]), economic-agricultural models (AgLink-SAPIM, IFPSIM-EPIC, and GTAP-CAPRI-FSSIM), economic–land-use models (GTAP-CLUE), and economic-environmental models (e.g., GTAP-CA-GREET).

Another tool to address the potential for multiple drivers and effects is through life cycle assessment (LCA), an approach designed to assess major impacts associated with all stages of a process from cradle to grave and including social, environmental,

[6] http://www.oecd.org/document/6/0,3343,en_2649_33777_36642246_1_1_1_1,00.html (accessed March 23, 2012).

[7] http://digital.library.unt.edu/ark:/67531/metadc13707/m2/1/high_res_d/Gusti_IIASA_model_cluster.pdf (accessed March 23, 2012).

[8] http://www.mnp.nl/en/themasites/image/model_details/energy_supply_demand/index.html (accessed March 23, 2012).

and economic effects (e.g., GREET,[9] Ecoinvent,[10] and GHGenius[11]). LCA often requires the results of many other models as input values. Some call these LCA approaches *spreadsheet models*, and their value may be in providing a means to link a whole set of model outputs into a common framework and to document the many influencing factors and their effects.

A common simplification underlying many models used to estimate land-use change is to assume that the change in land cover from one point in time to another is caused by the land use associated with the secondary observation. Thus if what was once classified as forest is subsequently classified as a soybean field, a causal relationship is assumed based on the observed correlation. In reality, the forces that determine whether land is cleared, how land is cleared, when land is cleared, and what is planted on the land after it is cleared are most likely to be quite distinct in each case and highly dependent on many site-specific contextual variables.

2.4. The Role of Data in Modeling Land and Carbon

Accuracy in modeling of land and C processes depends on the underlying data and relationship assumed to describe these phenomena. Obtaining data is often a challenge. Independent data for validation are not always available at the time the model is developed. In that case, any data that are readily available are often used to calibrate the model, and validation often must await new information. Furthermore, the number of observations available for validation is often less than the number of parameters. When only a small amount of data is available, the standard deviation in model parameters can exceed the variation being modeled, which may compromise the statistical validity of any simulated values.

Typically and not unexpectedly, there is a lack of fit between the model projections and the observations. Often the model intent is to portray the theory. Even so, this discrepancy may stimulate a reevaluation of the model, a reevaluation of the input data or the questions being asked of the model, or both. Any data set is but one interpretation of reality, and there are always concerns about the reliability of the data because of sampling bias, spatial and temporal aspects of the sampling, testing design, and so forth. Thus models offer one of many possible interpretations of relationships among variables – just as the sample data provide one perspective. The relation between model projections and extant data needs to be considered, and if there is no agreement between observation and model projection in trends, values, or direction, then the differences must be explained.

[9] http://www.transportation.anl.gov/ (accessed March 23, 2012).
[10] http://www.ecoinvent.ch/ (accessed March 23, 2012).
[11] http://www.ghgenius.ca/ (accessed March 23, 2012).

Historical data or data collected from an independent location can serve for validation. When projecting model outcomes to the future, and thus to unknown conditions, creative ways to validate the model must be devised. Often a model can be initiated under past conditions and used to project changes up to the present time (e.g., Zeng et al. 2008). Such hindcasts can then be compared to historical data so that confidence in modeling past conditions can be extended to projections of the future in a quantitative way (e.g., see Pontius and Neeti 2010). Hindcasting should use historical data from time periods during which the processes of interest were operative. In other words, a test of model validity is limited to the prevalent conditions associated with the historic data. Thus models cannot make "predictions" about a future based on past relationships and processes, when these key variables are changing. Examples of significant global changes include warming, precipitation regimes, atmospheric concentrations of CO_2, conversion of natural landscapes (such as coastal zones) to human uses, intensification of nutrient cycles, hydrological cycles, disturbance regimes, introduction of nonnative species into ecosystems, and species loss.

Some data are not appropriate for model validation. For example, two-point comparisons can easily misrepresent actual trends and processes. Similarly, small data sets that happen to capture a rare or extreme event value may bias data in one direction, whereas discarding the data may lead to an opposite bias. In addition, although models of ecological succession can be tested by data that contain changes over time in vegetation, C, or floristic composition (e.g., Pontius et al. 2008), if regular disturbances are a part of the system being modeled and yet did not occur at places from which the data were obtained, then those data would not be useful for model validation. In contrast, Doyle (1981) presents a case of using past hurricane disturbance for appropriate model testing.

A concern specific to modeling land and C issues is the underlying data used to set initial conditions and values of model parameters. Too often, data are used without considering the bias originating from data inventory and editing, the effects of data uncertainty on model projections, or the suitability of the data for the application. For example, average C stock values generated from protected forest research sites may not be representative of C stocks on lands being converted to agriculture, because the latter have often undergone decades of timber extraction and other minor disturbances leading up to their use for agriculture. Similarly, data for land cover are sometimes employed when land use is being modeled. This chapter focuses on information underlying land use because Chapter 7 discusses C in land-use models.

A major challenge for modeling land use is the paucity of reliable data at appropriate temporal and spatial scales. There is only limited information about how land is used or managed. Any given class of land cover or land use could have wide-ranging C storage, flux, and potentials. Indeed, variation within a land-cover or land-use class may exceed that between classes. In addition, variations in forest growth rates or density can alter conclusions about the GHG emission effects of changes in forest area (Rautiainen et al. 2011).

Remote sensing data from satellites, although illustrative of many changes in the landscape, do not typically provide the detail necessary to estimate above- or belowground C storage or flux and other key attributes, such as what land is best suited for production and what intensity of production the land can support (CBES 2009; see Chapter 5). Satellite imagery is limited to observed land cover during recent decades, and even then, differing sensors and data classification systems make change analysis challenging. Remote sensing is capable of generating data with high spatial and temporal resolution, although the raw imagery alone does not reveal how the land is managed or why changes in cover occur. Many changes in land use and management are not measurable from land-cover data, which may lead to a misinterpretation of change and effects.

Some scientists use census or survey data to supplement land cover, but that information often deviates widely among countries because of variations in definitions of land-use classes and inventory techniques (Grainger 2010). Nevertheless, if properly collected and reported, census data can provide a valuable source of information on land management that is highly relevant to C flux and assessment. Currently, the variability in crops and global land-management practices cannot be accurately modeled or documented, partly because no global data sets are available that consistently measure changes in well-defined vegetation categories at regular intervals (Grainger 2008), much less changes in above- and belowground C stocks over time.

The categorization of land types can influence model interpretation. Even the definition of forest can cause confusion (Colson et al. 2009). Huge variations in C stores and sequestration capacity can occur over time within a single land-cover category such as forest or pasture (Rautiainen et al. 2011). Simple definitions of land-cover categories usually ignore these dynamics and merely assign average values for attributes to each category and then assume an abrupt and complete change at an arbitrary point of class differentiation (e.g., when forest canopy falls from 10 percent to 9 percent of the measured area, the land-cover changes from that of average "forest" to that of average "pasture"). In this case, changes in land-cover classification are often inappropriately substituted for changes in "land use." Using these definitional shortcuts to characterize how changes in land use affect C may not have much relationship to real-world processes that govern C sequestration and storage. Significant variations in the C attributes that depend on the history of land-use practices and the variance of C within land-cover types are typically not a part of the analysis.

Another example is marginal land, which is generally defined as land that is not generating profits under a given set of conditions. Marginal and degraded land that was previously cleared but is not actively cultivated represents a large and poorly characterized resource that can be categorized in several ways. Specific attention should be paid to historic trends and fluxes of C and nutrients because these dynamics are poorly understood and yet form a critical component of any assessment of potential land uses and C storage. Over the past two decades, an average of 3.8 million square kilometers of land (an area larger than India) was burned each year (Giglio et al. 2010), and most of the fires occurred on marginal lands in sub-Saharan Africa and agricultural frontiers in other developing nations. These lands clearly have great potential to sequester or release C, depending on management practices. In particular, characterizing the extent, location, and factors leading to land underutilization is necessary to design policies that can guide decisions about desired directions (e.g., to reduce total GHG emissions and to improve rural economies) (CBES 2009).

Consistent and precise information about C stocks, nitrogen stocks, and land-use- and land-cover–specific fluxes of C and nitrogen are not available at the global scale. Standard data sets are needed for validation or verification of model results from back-casting or other approaches; however, adequate validation of global models may not be feasible in the near term because of data limitations. The global land-change modeling community requires spatially explicit land-use data updated on a yearly or seasonal basis with special attention to marginal lands and connecting, where possible, the land-use management data available from local agencies to observed land-cover information (Ramankutty et al. 2008) along with corresponding biogeochemical fluxes associated with these uses and cover types.

3. Using Models in Making Decisions about Land and Carbon Cycling

Models can be valuable tools for increasing understanding about interactions between land use and the C cycle, or they can foster misconceptions. Overreliance on models can have consequences ranging from misinformation that undercuts efficient assessment of water quality (e.g., the Chesapeake Bay; Shivers and Moglen 2008) to financial calamity (discussed later). Hall (1988) points out that decision makers sometimes accept model results without considering how they relate to the real world. Models offer several advantages for guiding decisions in land-use and C management, but they should be employed with a certain amount of caution.

3.1. Advantages of Using Models to Increase the Understanding of Decision Makers

Quantitative models, when run in a deterministic mode, are repeatable. They are able to integrate known information from several different sources and disciplines and thus can address the broad constraints, conditions, and opportunities with which decision makers are presented. Often, decision makers have to address issues that require attention at different temporal and spatial scales. Some models focus on processes that occur on the order of seconds to minutes (e.g., how land use can affect air quality), whereas others consider changes on the timescale of decades, centuries, or millennia (e.g., return interval of fires, droughts, or climate change).

Models that help to explain the dynamics behind changes over years to decades are most in demand by decision makers dealing with land and C issues because they match political time horizons and because many of these effects are not apparent for many decades or even centuries. In any case, the timescale of a model needs to relate to the timescale of the management questions and their implications. Furthermore, the specific management issue targeted by a modeling project focuses the spatial scale of the question and points to the type of model to be used as well. Although some management issues deal with decisions on small scales for homogeneously managed land, it is often necessary to consider a parcel within a larger context because past management of the parcel along with past, present, and future activities on adjacent lands may have influences (White et al. 1997) and because natural and political boundaries also come into play.

Models can help to organize and track information, ideas, and the outcomes of decision-making experiments in a way that would not be possible otherwise. The act of writing an equation explicitly defines relations and formalizes the hypothesis being explored. Mathematical models are useful to explore relationships in cases where field or laboratory data are limited, incomplete, or not directly applicable to the decision being made. In those cases, results from mathematical models can provide a perspective on alternative choices. Even when extensive data are available, the complexity of a situation may require a model for interpreting interactions or expanding results to larger spatial scales or longer timescales. The absence of adequate data does not imply that there is no scientific value in developing models of land use or C flux. The collaborative process of scientists developing a simulation model can be worthwhile, because it requires synthesis of data, theories, and opinions over scales of space, time, and biological organization. It often results in questions appropriate for new experimental studies, particularly when models do not meet expectations (Aber 1997). Furthermore, it can help to focus efforts on priorities for data collection and analysis.

The advantages of model experiments and scenario analysis may be particularly useful to decision makers and other stakeholders designing steps to use market and financial incentives to reduce the emissions of GHGs from deforestation and forest degradation (REDD). REDD objectives often include conservation, biodiversity, and alleviation of poverty. Modeling of land use is needed (1) to identify and assess the practices that would have occurred without a REDD Project intervention (the "business as usual" scenario) and (2) to compare the effects of that scenario with what would happen under alternative policies designed to reduce GHG emissions (Brown et al. 2007). REDD-related research efforts have revealed some of the different drivers of land-use change around the world (e.g., in Panama: Dale et al. 2003; Indonesia: Butler, Koh, and Ghazou 2009; Uganda: Nakakaawa, Vedeld, and Aune 2011). REDD activities have typically been undertaken by national or local governments with support from external partners such as Norway, the United Nations, and the World

Bank. However, it is the people living in an area where REDD activities occur who are most affected, because their livelihoods typically depend on the forest. Hence, modeling land-use change with respect to C fluxes and REDD is likely to be more useful if it incorporates an understanding of local social, cultural, and political conditions and aspirations. Properly designed models, along with participatory approaches, monitoring, and other tools, could help to guide investment decisions that benefit indigenous people and conserve natural resources while providing a point of reference for a political process dealing with the causes and effects of deforestation (Corbera, Estrada, and Brown 2010).

3.2. Cautionary Principles in Using Models for Decision Making

Great caution is required in interpreting model projections, and decisions should not be based solely on model results because model projections are representations of a selected set of observations of the real world based on the existing scientific understanding of the system (Dale and Van Winkle 1998). Effectively used, calibrated, and validated, these results can provide information regarding what *could* happen, not necessarily what *will* occur in the real world.

Model results always have uncertainties because they are based on simplifications of processes and their interactions. That is why model results are called *projections* (estimates of future possibilities) rather than *predictions* (something that is declared in advance) (Dale and Van Winkle 1998). Even so, decision makers and the public typically do not recognize the great uncertainties in land-use changes as sources of GHG emissions (estimates of the annual flux of CO_2 released through forest clearing are uncertain by plus or minus 200 percent according to the NRC [2010]). Decision makers need to understand how models fit within the process of scientific investigation. Developing scientific knowledge is an iterative process that builds from observations to formulate hypotheses that can then be tested with empirical information or, in an interim period when data are lacking, with models. Additional data collection, research, and analyses lead to new understandings and new hypotheses, which, in turn, are often further revised in the future. Thus models do not present “truths” but only an interpretation of the underlying assumptions and scenarios being explored at a given point in time.

Model results are often presented to decision makers as possible implications of a certain set of assumptions that characterize a future scenario. Frequently, several scenarios and their implications are presented as a way to capture a range of future possibilities (e.g., Intergovernmental Panel on Climate Change [IPCC] 2000). In such cases, scenario analysis is used to explore alternative futures. Because the future is unknown, it is important to consider several scenarios and to base at least one scenario on “business as usual.” Although changes occur in all situations, an extrapolation of recent trends can be used as a point of reference in many situations. An example of this approach occurred in the Brazilian state of Rondônia (Dale et al. 1994), where a model was developed to identify the effects of farmers' decisions on C sequestration. The model assessed the ability of those farmers to remain on the land and found that the business as usual (slash, burn, cultivate, deplete the soil, and move on) scenario was more similar to the "unsustainable" scenario than to "sustainable" scenarios that involved the use of multiple perennial crops and no burning. These model results helped to support the government's plan to establish farmers who used multiple perennial crops and did not burn as a way to show other farmers how to manage land for persistent productivity and to enhance C sequestration. Such scenario exploration informs policy makers about which aspects of the systems they should be most concerned.

Current understandings of complex systems, as reflected in models, are rarely adequate to provide answers to decision makers' questions. There is no simple theory to describe all the complexities in land-use processes (Veldkamp et al. 2001, CBES 2009). The sophistication of numerical models and accompanying sensitivity analysis and "error bars" can lead to a false sense of confidence and may inhibit people from questioning the applicability or accuracy of results. Often it is necessary to move ahead in the decision-making process with incomplete information (Wiens 1996). Models may be able to provide some insights; however, they cannot provide predictions about particular outcomes when new forces are at play. In such cases, models can be used to inform decision makers about potential issues and outcomes, but it is critical that the limitations of models and their projections be made clear.

Although this book focuses on the topic of land use and the C cycle, the role of models in the 2008 global financial collapse provides some lessons regarding the use of models for integrating science and decision making. In July 2009, *The Economist* featured a series of articles titled "What Went Wrong with Economics?" that led to a debate about the appropriate role of models and modeling. Unlike global land-use change, the financial markets are regulated, carefully tracked, clearly defined in monetary values, and supported by extensive accounting and records. Such a system is far simpler and more disposed to modeling and verification than C and land use. One key problem leading to the financial crisis was excessive reliance on models representing complex security derivatives and hedges that were not adequately understood. In addition, some models were fit to historic data that did not measure critical phenomena and were based on inappropriate assumptions (e.g., assuming growth and stability in perpetuity for home mortgages). Finally, the models were not routinely calibrated to account for stochastic events or nonstationarity in the processes they represented. A major collateral problem identified was lack of attention to and analysis of accumulating empirical evidence (e.g., excessive growth in housing stock). Jean-Luc Demeulemeester and Claude Diebolt (2009) therefore urged decision makers to "take models for what they are: simplified views of the world that help us think about a complex issue, but are not true representations of the complexity itself."

Experiences in the finance sector offer a cautionary note to policy makers who must rely on models. As George Box (1979) noted, we must realize that "all models are wrong; some are useful" (p. 202). The lessons from modeling in the financial sector underscore the need to have a good understanding of the underlying model and the data supporting it and to compare model simulations with the empirical evidence to avoid serious errors. When models are used to estimate C changes associated with land cover and land use, these caveats merit serious attention.

3.3. Communicating about Models to Decision Makers

Models are quite useful for communication because they are often designed to describe how elements of a system respond to policy alternatives. Developing a model requires defining and quantifying key drivers of a system and determining how they interact. It also calls for selecting a theory on which to base the model and to formalize the underlying logic.

Models need to be understood not only by those developing and applying them but also by decision makers and society. Based on his experience in using mathematical models in courtroom situations, Swartzman (1996) points out:

- The model must make common sense.
- The model must be simple enough for nonscientists to understand.
- Jargon must be avoided.
- The model and its projections must be clearly described; simple illustrative graphics are most helpful.

These lessons are general enough to be applicable to decisions about land and the C cycle. However, to capture key processes accurately, modelers must make models more detailed and complex, whereas decision makers want models to be more understandable. This situation produces tension in applied modeling.

Model results are often not used in decision making because they are poorly understood. Many of the challenges related to model use arises from unrealistic expectations (Van Winkle and Dale 1998). Discrepancies between reality and model projections arise, in part, from a lack of decision makers' understanding of the model assumptions, the scientific process, the uncertainty in the model projections, the variability in the natural system, the immaturity of theory, and factors that were not included in the model but that influence the outcome of decisions. Other times, model results are adopted with too few caveats about their interpretation or validity.

One way to improve decision making supported by models is to increase communication between the decision makers and the modelers and scientific disciplines that support the analyses related to the policy issue at hand. Ways to enhance communication include workshops, presentations, white papers, and understandable and accessible documentation. Such steps can create more realistic expectations of the contributions of models. Understanding the outcome of a model is not achieved just by examining the graphical, mapped, or tabular output but also by being aware of the strengths and limitations of the particular modeling approach, the assumptions, and the uncertainties in the projections (Dale and Van Winkle 1998). Decision makers should be briefed on specifics of model documentation (see Table 8.1) and need to know the quality of the underlying information. However, decisions must frequently be made in the face of uncertainty. It is in those instances that the modeling process may be most useful.

Decision makers need to be regularly informed that models based purely on theory or that combine qualitative and quantitative information cannot provide reliable or valid quantitative predictions because they never include all influences in a system. Models can provide estimates and suggest trends regarding the direction of change and the relative importance of different processes and parameters; however, results are no more reliable or valid than their underlying data and assumptions. Therefore, it is important for policies and decisions to have clearly defined goals and a systematic approach for monitoring progress toward those goals based on empirical data and analysis that are independent of models.

Integrating models into decision making requires (1) developing flexible approaches to presenting and applying the results and (2) making the models and modeling results available and understandable to landowners and resource managers. For such applications, models may need to be designed up front to meet the specific needs and skills of the users and to accommodate new data and understanding as they develop. There are many different models, and most were developed for a specific, narrow purpose or to test the influence of a single attribute or factor of change among many others. However, when new needs and questions arise, there is a tendency to use existing models and other tools that are readily available. It is much easier to use an existing model than to conduct years of data collection and scientific analysis or to create a new model designed for the current concern. If existing models are adopted to address land- and C management concerns, then those models should be adapted to reflect not only the economic processes involved but also the biophysical processes, land-use history and trends, local cultural traditions, and socioeconomic and time constraints of the people occupying and managing the land.

4. Conclusions and Opportunities Ahead

Properly designed and applied, models can support the process of exploration and refinement of land-management options and improve understanding of underlying processes. However, it is critical to follow basic procedures for modeling so the assumptions of models are clear, the models are tested and validated with appropriate data (when possible), and the range of applicability of the model projections is made clear. In any case, gaps among claims, expectations, and the roles of models and the modeling process need to be pointed out to the user when these tools are used in policy and management. Furthermore, it is extremely important not to confuse model projections with scientific results. Models support decision making by helping to overcome human limits in the ability to assimilate, process, and interpret data without bias but are never a substitute for the human decision process.

Opportunities exist to improve modeling of land-use change and the C cycle so that the scientific understanding and information on these issues is presented in a way that is more useful to decision makers. Specific suggestions include:

- Modeling at the appropriate spatial and temporal scale (while considering changes that might occur at least one scale up and down)
- Following appropriate modeling procedures (see Table 8.1)
- Focusing on elegance of the approach – that is, including and identifying the necessary information and processes and avoiding unnecessary detail; encouraging the collection of data to validate the model and its projections
- Communicating the results, sensitivities, and uncertainties to both scientists and policy analysts (and recognizing the different ways to do this)
- Developing a new ontology of land classifications based on empirical measurements of C stocks, fluxes, and capacity for future storage
- Applying the ontology to establish a global reference data set of high geospatial and temporal resolution (A common reference system is needed to permit improved analysis of changes associated with land use and to allow comparisons of model results, and current land-cover and land-use classifications and data sets are inadequate to meet C modeling demands.)

Models are often an integral part of scientific development and management, and a variety of tools are available for developing, testing, and implementing models. Because land changes are spatially dynamic, it is useful to use mapping and spatial analysis to document change. A variety of visualization approaches can be used for communication, validation, or sometimes extrapolation (e.g., Pontius, Huffaker, and Denman 2004; Pontius, Versiuis, and Maizia 2006). The steps and components of the modeling process are straightforward but not always applied. Too often, the use and value of models do not extend far from the communities of researchers who develop these models. Therefore, this review suggests a need for the following:

- Understanding that models can be a part of the management process that includes exploration and refinement of management options
- Involving field researchers and other local stakeholders in the process of developing model assumptions and input values
- Properly documenting models using standardized procedures
- Adopting interdisciplinary approaches for complex issues such as land-use change
- Framing the question appropriately for the policy needs
- Using models that are appropriate for the question
- Educating decision makers about the scientific process

Key challenges include (1) the development of spatial and temporal data sets at resolutions that provide accurate representation of historic changes in C stocks, C flux, and C storage capacity associated with geospatially explicit land-management projections; (2) balancing the complexity of dynamic historic changes, uncertain future climate conditions, global markets, and development with the need for clear and simple representations of the causes and effects of land-use change; and (3) providing clarity to decision makers on the differences between best available science and best available models.

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