Chapter 4

State of the Art in Simulating Future Changes in Ecosystem Services

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TABLES

Main Messages

Building scenarios and anticipating changes in ecosystem services are modeling exercises. The reliability of models depends on their data inputs and the models themselves. This chapter sketches out the state-of-the-art modeling approaches for critical components of the Millennium Ecosystem Assessment scenarios, examines strengths and weaknesses and alternative approaches, identifies critical uncertainties, and describes high-priority research that could resolve fundamental uncertainty.

In order to evaluate the MA scenarios, readers must understand the capabilities, uncertainties, and frontiers of the models used to project changes in ecosystem services. This chapter provides a rigorous scientific discussion of just how confident we can be about different dimensions of the scenario model analyses and where we need to do a great deal more work. Uncertainty is acceptable as long as it is acknowledged up front. Although many of the models used to inform scenarios have weaknesses, the alternative is to use no models whatsoever. The modeling approaches and the uncertainties vary according to topic. Hence we take up the modeling issues one topic at a time, forecasting land cover change, impacts of land cover changes on local climates, changes in food demand and supply, changes in biodiversity and extinction rates, impacts of changes in phosphorous cycles, impacts of changes in nitrogen cycle and inputs, fisheries and harvest, alterations of coastal ecosystems, and impacts on human health. The final sections evaluate integrated assessment models and look at key gaps in current modeling abilities.

The uncertainties and limitations of models are extensive, and in many cases proven methods do not exist for the forecasting tasks that we face. Recurring limitations and constraints include an absence of models that work well across multiple scales, failure of models to couple interacting processes, and models based on nonrepresentative subsets of Earth's ecosystem services (such as specific and narrow taxonomic groups or geographic regions). These limitations do not mean we should not attempt to make a forecast—only that we should present results with appropriate levels of uncertainty. The act of attempting to make forecasts where apt methods do not exist has already spurred enormous research and innovation, such that in five years our forecasts will become much more reliable. For this reason, we pay particular attention to advances in modeling or data that are likely to greatly enhance our ability to assess alternative ecosystem futures. It is important to recognize that models are not statements of fact but instead are hypotheses to be evaluated in light of coming changes in ecosystem services.

4.1 Introduction

The models used to generate scenarios for the Millennium Ecosystem Assessment are not the only models available. This chapter examines state-of-the-art modeling approaches for critical components of the MA scenarios. It considers the suite of models and modeling approaches that might be drawn on for scenario analyses. The four core models actually used for the global MA were IMAGE for land use change, IMPACT for food demand and agriculture, WaterGAP for water use and availability, and EcoPath and Ecosim for predicting fisheries impacts. (See Chapter 6 for more-detailed descriptions of the models.) In many cases these models were chosen because they are the only ones with global coverage (WaterGAP, for instance).

The state of the art for environmental modeling is changing very rapidly. This chapter describes the key modeling arenas in which we expect major advances over the next 10 years, which in turn could provide improved tools for future global ecosystem assessments. Hence we discuss some models, such as for phosphorous cycling, for which there is no global model but where progress is expected so that future global assessments will have new tools. Climate modeling is not covered, since there have been numerous review papers describing the existing climate models.

In general we seek in this chapter not to advocate or defend the MA's choice of IMAGE, IMPACT, WaterGAP, and Ecosim/Ecopath. Rather, we provide readers with an overview of the modeling field and the variety of approaches being pursued, with pointers to where we expect future research will lead. This venture is so new that there is no commonly accepted suite of models or, as is the case for climate models, some standard approach for testing and contrasting the performance of competing models. In some cases the actual models used by the MA are virtually all that is available. In other cases, such as in models for predicting biodiversity change, there are a variety of options, all under current research development.

The major types of models are:

- statistical models that rely on observed relationships and extrapolate into the future;
- first-principle equations that solve for equilibrium or draw on fundamental laws of transport and mass balance;
- large system (usually simulation) models that mathematically describe relationships among a web of state-variables and attempt to include a somewhat complete representation of the drivers of change;
- expert models and decision support systems that translate qualitative insights or expertise into quantitative assertions; and
- a wide variety of ''agent-based'' or cellular automata models in which the activities of individual actors are simulated and then aggregated to understand whole-system behavior.

This is not the only taxonomy of models; alternative distinctions include stochastic versus deterministic, simulation versus analytical, spatial versus nonspatial, equilibrium versus nonequilibrium, and so forth. But these categories are most germane to the strategic choices available when attempting to perform a global scenario analysis. We have made an effort to remove as much technical language as possible. We obviously have not succeeded as well as would be ideal. However, in many cases what appears to be ''jargon'' is necessary for precision and to help other technical experts know exactly what modeling issue is under discussion.

This is not a chapter for light reading. This is a chapter to read with the idea of learning what is going on in the modeling world that might be important for future assessments. The topics chosen are not encyclopedic. We structure discussion around core modeling arenas (such as fisheries or land use or agricultural production). One of the biggest areas of modeling research is coupling models of different processes together and attempting to incorporate feedbacks among processes. Figure 6.3 in Chapter 6 shows how the MA linked together to model different processes.

In the future there may be many more options, and in fact one conclusion of this chapter is that the linking of different processes and scales is probably the biggest research need.

When considering each section, it will be obvious that none of the modeling approaches is ideal. Compromises must be made because of lack of data. Documentation of large-system models is often weak, and transparency is not all it should be. Although many of the models considered for use in the MA are for forecasts, they are also hypotheses, as all models are. This chapter seeks to introduce some alternative approaches that might be selected if existing models fall short. As data are collected, we expect some models to be rejected and new ones to be used. One outcome of the MA is pressure for better modeling practices.

4.2 Forecasting Changes in Land Use and Land Cover

Land use change models attempt to project future changes in land use based on past trends and the drivers thought to determine conversions of land between different categories (forest to agriculture, agriculture to urban, and so forth). One initial motivation behind land use change modeling was the prediction of tropical deforestation, with its many consequences. The field has now broadened geographically and with respect to the type of land cover transitions it examines. Central to understanding the human and ecological aspects of land use and land cover change (or land change) is a movement toward an interdisciplinary perspective of change, where social, ecological, and information sciences are joined (Liverman et al. 1998; Gutman et al. 2004). A core component of integrated land change science is formed by spatially explicit, dynamic land change models that explain and project land cover and land use changes (IGBP-IHDP 1999; Veldkamp and Lambin 2001). Given that land use and land cover are dynamically coupled, land change models provide one of the more powerful ways to combine human and biophysical subsystems, permitting assessments of the consequences and feedbacks between the subsystems. In this sense, these models improve understanding of a broad range of issues critical to the MA, from the resilience of ecosystems to human perturbations to society's responses to changes in ecosystem services.

Land change models are generally classified according to their implementation or scale (e.g., Lambin 1994; Rayner 1994; Kaimowitz and Angelsen 1998; Agarwal et al. 2002). They tend to use a variety of data sources as input. Survey and census data have long been used by land change models and are increasingly joined by spatial data (maps, for instance) on land manager activities and socioeconomic factors. These spatial data are often used in the context of geographic information systems—software systems that store, manipulate, and analyze georeferenced data—and are derived from sources as varied as remotely sensed imagery and global positioning system receivers. Data are also increasingly gathered over several time periods in order to aid understanding of land change trajectories. The chief output of land change models tends to be explanations of past and present use and projections of future land use.

4.2.1 Existing Approaches

Perhaps the simplest land change models use a non-iterative set of equations to seek a single solution where the modeled system can be characterized as static or existing in equilibrium. Gravity models or logistic functions, for example, are used to estimate population-driven land conversion over large areas and coarse resolutions. These models are often based on theories of population growth and diffusion, processes that are thought to determine cumulative land change (Lambin 1994).

System models typically represent stocks and flows of information, material, or energy as sets of differential equations linked through intermediary functions and data (Hannon and Ruth 1994). When differential equations are numerically solved, time advances in discrete steps, which in turn allows dynamic representation of feedbacks so that interacting variables can influence one another's future dynamics. Earlier system models of land change were not spatially explicit, but more recent models are increasingly linked to spatial data (e.g., Voinov et al. 1999; Zhang and Wang 2002).

Another group of land change models relies on statistical methods based on empirical observations (Ludeke et al. 1990; Mertens and Lambin 1997; Geoghegan et al. 2001). For example, econometric models use statistical methods to test theoretical hypotheses concerning the consequences of new road systems (Chomitz and Gray 1996; Nelson and Hellerstein 1997; Pfaff 1999) and of other economic and ecological variables exogenous to the modeled system (Alig 1986; Hardie and Parks 1997). Unless statistical models are tied to a theoretical framework, they may underrate the role of human and institutional choices (Irwin and Geoghegan 2001).

Expert models express qualitative knowledge in a quantitative fashion, often in order to determine where given land uses are likely to occur. Some methods combine expert judgment with Bayesian probability (Bonham-Carter 1991). Symbolic artificial intelligence approaches, in the form of expert systems and rule-based knowledge systems, use logical rules in combination with data to grant models some capacity to address novel situations. Lee et al. (1992), for example, use probabilities to build a set of stochastic branching rules regarding possible land transformations, and then connect those rules with an independent ecological model to assess land change impacts. The probabilities for these branching rules are not estimated in a traditional statistical sense but instead are inferred by interviewing numerous land managers and synthesizing their answers into probabilities.

Land change models that are based on biologically inspired evolutionary computer modeling methods are increasingly common (Whitley 2001). Perhaps the most promising are models based on artificial neural networks, computational analogs of biological neural structures (such as the neuronal structure of the human brain), which are trained to associate outcomes with given stimuli, such as associating spatial land change outcomes with inputs like population density or distance to water bodies (e.g., Shellito and Pijanowski 2003). Another body of research applies computational models of Darwinian evolution, such as genetic programming or classifier systems, to tease out causal linkages between various factors and land change (Xiao et al. 2002; Manson 2004).

A growing number of land use and land cover change models are based on cellular modeling methods, which use models that conduct operations on a lattice of congruent cells, such as a grid. In the common cellular automata approach, cells in a regular two-dimensional grid exist in one of a finite set of states, each state representing a kind of land use, for instance. Time advances in discrete steps, and future states depend on transition rules based on a the condition (or state) of the surrounding immediate neighborhood (Hegelsmann 1998). In another common cellular modeling method—Markov modeling—the states of cells arrayed in a lattice depend probabilistically but simply on previous cell states. Cellular models have proved their utility for modeling land change in linked human-environment systems (Li and Reynolds 1997; White and Engelen 2000).

Agent-based models are a relatively recent development in land change modeling. They are collections of agents, or software programs, which represent adaptive autonomous entities (like farmers, or institutions that build roads, or local elders) that extract information from their environment and apply it to behavior such as perception, planning, and learning (Conte et al. 1997). Agent-based models have been used in particular to model small-scale decision-making of actors in land change (Gimblett 2002; Janssen 2003; Parker et al. 2003).

4.2.2 Critical Evaluation of Approaches

Equation models have the advantage of being simple and elegant and relatively transparent. These models can provide a good first estimate of land change at broad scales, which can be tied to driving forces such as population or economics. Their chief limitation is the degree of simplification necessary to create an analytically tractable system of equations, which often results in a highly abstract model that does not reflect many aspects of reality (Baker 1989). Cross-scale relationships (interactions between different spatial scales) and time-dependent relationships can be difficult to model with simultaneous equations, given the need for common parameters across scales or time and equilibrium assumptions.

System models are a powerful means of representing dynamic systems. They are widespread across many academic disciplines. System models can face limitations, however, because the complexity of real-world parameters can be difficult to convey in the form of linked equations. Equations can also limit system models to statistically idealized flows and stocks, which means that discrete actions or the decision-making that led to them are not included unless the system in question is modeled at a small scale or in detail (Vanclay 2003). In order to focus on key dynamics, the modeler typically makes assumptions about the aggregate results of behavior at the potential cost of glossing over or assuming away key system behavior.

Statistical models are widely accepted and well understood. Despite this, considerable care must be taken to ensure assumptions such as independence of observations, especially in light of spatial or temporal autocorrelation (where observations are correlated in space or time) (Griffith 1987) and issues of data aggregation (combining data from multiple sources or scales) (Rudel 1989). Researchers have begun to devote attention to the statistical problems that arise from using spatial data, thereby decreasing the bias and inefficiencies in parameter estimates and using spatial and temporal autocorrelation to inform model construction (Kaufmann and Seto 2001; Overmars 2003). Another complication is that the choice of a land change descriptor can dramatically influence the result, such as when tracking change in areal extent of land cover, as opposed to the rate of change in land cover (Kummer and Sham 1994). Either variable is correct in the sense that it measures phenomena of interest, but the variables can give different statistical results.

Expert models are useful for rendering qualitative expert domain knowledge into formats traditionally considered quantitative knowledge. The underlying logical basis that allows these models to function can create difficulties, however, since it is challenging to include all aspects of the problem domain, which can lead in turn to inconsistencies in model results. Application of expert systems to land change has remained underexplored due to the difficulty of logically encoding knowledge that adequately maps onto the complex spatiotemporal nature of most land use and land cover change situations. Similarly, it can be difficult to find experts sufficiently versed in a given situation; when they are found, it is also difficult to parse their knowledge into the logical rules and structures necessary to create expert models (Skidmore et al. 1996).

Evolutionary models have been used with success to project land use and land cover change. They are in essence powerful directed-search methods that excel in identifying patterns and relationships in highly dimensional, noisy, stochastic environments (Kaboudan 2003). At the same time, theories on how and why evolutionary methods work are subject to ongoing debate, which serves to blunt the edge of any analysis based on them (Whitley 2001). One side effect is that identification of structures of causality and correlation is more straightforward with statistical methods, for example, than with evolutionary methods because the latter can too easily be used to create convoluted computer programs that produce seemingly good results but at the expense of understanding how or why.

Cellular models are appealing for their capacity to use relatively simple rules to represent local interactions that can in turn lead to complex outcomes (Phipps 1989). Cellular models can suffer from ''spatial orientedness'' (Hogeweg 1988), however, where the simple cellular neighborhood relationships do not reflect actual spatial relationships. As such, these methods may not be suited to model land change where there are non-uniform or non-local interactions. As a result, they must be buttressed with complex rule sets to differentiate between the kinds of decision-making that apply to groups of cells, such as local land tenure structure (e.g., Li and Gar-on Yeh 2000). While effective, these deviations from classic cellular models come at the potential cost of moving models away from their key advantage of simplicity (Torrens and O'Sullivan 2001).

Agent-based models typically complement other approaches to modeling land change. Their strength lies in the ability to represent heterogeneous agents (Huston et al. 1988) and to incorporate interaction and communication among agents (Judson 1994) in a manner unlike that of other modeling methods. Agent-based models can be difficult to use, however, since they are often tailored to a particular setting and create results that are often not generalizable (Durlauf 1997). Much work remains to be done on establishing common modeling platforms and devising means of validating agent-based models, particularly when distinguishing legitimate results from modeling artifacts, as many of these models remain underevaluated. Similarly, they are often used at small spatial scales; they need to be scaled up to larger ones useful for full ecological assessment (Veldkamp and Verburg 2004; Manson 2003)

In sum, modeling land use change runs the gamut from relatively straightforward equation-based models to complicated and computationally intensive models. There is a movement toward greater integration and hybridization of these approaches in order to compensate for shortcomings of individual methods and to address outstanding issues in land change, such as interdisciplinary integration, spatiotemporal scale issues, and the complexity of land change (Brown et al. 2004).

Dynamic spatial simulation modeling, for example, incorporates cellular modeling to address spatial heterogeneity and uses system models to represent social and economic mechanisms in addition to ecological processes such as secondary succession (Lambin 1997). GEOMOD2 combines statistical modeling, systems approaches, and expert decision rules to project land change at the regional scale (Pontius et al. 2001). Another example is given by the CLUE family of models, which use a combination of approaches to model land change and associated phenomena at regional scales (Veldkamp and Fresco 1996; Verburg et al. 2002). A final example is found in Integrated Assessment Models that incorporate links to the terrestrial environment at continental and global scales. The IMAGE 2.0 model, for example, incorporates land use, land use change, soil information, and element fluxes at the global scale at half-degree resolution (Alcamo 1994). Integrated Assessment Models are discussed at the end of this chapter.

4.2.3 Research Needs

The future of land change modeling is defined in part by three themes: interdisciplinary research, better integration of theory and method, and refinement of modeling techniques, including establishing standard rules, measures, and metrics that provide the rigor found in less expansive modeling approaches common to established subfields (such as demographic or econometric models) (Rindfuss et al. 2004). First, integration across disciplines appears increasingly necessary with respect to understanding the webs of causality underlying land change. The land change research community has identified three conceptual foci: social systems, ecological systems, and land managers or decision-makers (IGBP-IHDP 1995). Heretofore, social systems such as institutions (rules) have not been incorporated well into human-environment models. Land change models, however, increasingly account for institutional settings, thereby increasing their robustness for use at local to regional scales of analysis (Gutman et al. 2004).

Second, it is increasingly apparent that land change modeling can be improved and can create greater interest among the core social and environmental sciences if it is informed by critical concepts and theory relevant to both sciences and their coupling. Irwin and Geoghegan (2001), for example, argue that land change models often claim to represent human behavior while not explicitly using theories of human behavior. Similarly, other models proclaim to address the environment, but it is reduced to nature as a resource stock for human use, not as part of a functioning ecosystem. There is therefore an increasing focus on incorporating ecosystem models, such as landscape-scale forest models, with models of land use (He 1999). Greater engagement across disciplines will likely (or it is hoped will) accelerate the trend of better integration of theory and method.

Third, the greater integration and hybridization of the approaches noted earlier speaks to ongoing development of new methods and metrics of performance. It is important to note that models are increasingly oriented toward pursuing the fine spatial and temporal resolution necessary to assess human dynamics, such as individual decision-making, and ecological phenomena, such as biodiversity. Having both temporal and spatial explicitness is a key need, and therefore a goal, of land change modeling (Agarwal et al. 2002). Getting the magnitude of land change right is only part of the goal; getting its location right is the other. Model performance regarding both needs requires new metrics (Pontius 2000).

Also important is the extent to which models can also serve as vehicles to integrate disciplines in a manner that captures interactions across various real-world human and environment systems. Most of these methods, for example, can incorporate some degree of feedback between human and biogeophysical systems. Some do so explicitly, such as system models or cellular models, while others, such as expert models or agent-based models, have been adapted to accommodate dynamic interactions.

Finally, there is a movement toward increasing model transparency through mechanisms, such as better user interfaces and communication of model results both in and out of the research community (Parker et al. 2003). The key stumbling block to incorporating these changes resides less in the models themselves and more in the disciplinary contexts in which they are used. This caution notwithstanding, land change models promise to provide the foundational basis for understanding and projecting human-environment interactions for terrestrial ecosystems.

4.3 Forecasting Impacts of Land Cover Change on Local and Regional Climates

Terrestrial ecosystems both influence the climate and in turn are themselves influenced by the climate (Foley et al. 2003). Scenarios of the future paths of the biosphere (e.g., DeFries et al. 2002a) must therefore be viewed as interactive with the climate system. A detailed analysis of this issue would require intertwining Intergovernmental Panel on Climate Change predictions and dynamical representations of future greenhouse gas emissions and their impacts on climate with a MA-type model of vegetation and biotic responses that in turn fed back on the greenhouse gas scenarios. Such an analysis is currently not feasible. However, a general awareness of the techniques that might be used should promote improved treatments in future assessments. (Various anthropogenic processes that drive climate change and can feed back on the biosphere are discussed extensively in Chapter 13 of MA *Current State and Trends*.) An earlier review from a climate modeling perspective is given in Dickinson (1992).

What are the changes of land use that may significantly affect climate? They include conversion of natural forest to other uses, including agroforestry, grazing, and crops; conversion of grasslands by natural or human factors to other covers, including shrubs (e.g., Hoffman and Jackson 2000) and croplands; desertification; initiation or cessation of irrigated agriculture; urbanization; draining or creation of seasonal or permanent wetlands; and, in general, anything changing the overall vegetation density, commonly expressed in models by its leaf-area index, or changing the hydraulic or nutrient properties of the soil (such as compaction or salinization).

Discussion here is limited to the question of the current modeling basis for describing how changes in human land use can modify climate. Any quantification of the future impacts on climate of land use change must start with predictions or scenarios of land use change. These changes must be described in terms of the parameters that characterize the impacts of land on climate through biophysical (that is, energy and water balance) or biogeochemical effects (modifying the atmospheric gaseous or particulate composition). Chapter 13 in the MA *Current State and Trends* volume addresses current knowledge as to land use change modification of climate drivers. Here, we focus on the assessment of the capabilities for future prediction, assuming we have appropriate information on current conditions (which in reality we may not always have).

Describing the biophysical impacts of land use and land cover change on local and regional climate is an area where the general modeling strategy and methodology is relatively free of controversy. A single modeling approach—based on global and regional climate models—is accepted as credible, so the assessment task is a judgment as to which implementations of this method are likely to be most successful. However, application of these models to the question of the impacts of land cover change on climate is sufficiently immature that their evaluation has been limited. In other words, any such application may provide useful guidance, but details would have to be presented with ample caveats and with considerable uncertainties. The most serious bottlenecks for progress are quantification of scenarios of future land use and land cover change in terms that provide parameters needed by the models, the lack of test cases with which modeled impacts of land use/land cover change have been compared to observations, the absence of a full incorporation of feedbacks from changes of vegetation cover in climate simulations, and uncertainties in the treatment of the coupling between land cover change and atmospheric boundary layer processes connected to rainfall.

Biogeochemical connections to terrestrial ecosystems are detailed in Chapter 13 of the MA *Current State and Trends* volume and various management strategies are indicated in Chapter 12 of the MA *Policy Responses* volume. This brief overview of the biogeochemical consequences of land use change indicates what should be included as output of such modeling: The terrestrial system includes important stores of carbon that through land use change can become sources for greenhouse gases or other significant atmospheric constituents. In addition, terrestrial processes can sequester carbon dioxide from the atmosphere and so reduce the impact of that added by fossil fuel combustion. The release of methane to the atmosphere by carbon cycling in anoxic soils can be modified by land use change. Land use change that extends livestock grazing may increase methane emissions. Changes may also occur in the release of volatile organic compounds and so affect air quality or the formation of aerosols, and the latter may have impacts on cloud formation and precipitation.

4.3.1 Existing Approaches

4.3.1.1 Climate Models as Used to Address Biophysical Impacts of Land Cover Change

The only general approach to assessing impacts of land use/land cover change on climate that has a good likelihood of providing useful information from a policy viewpoint is a comprehensive approach that integrates global or regional climate models. Such integration is only likely to be credible if its starting point is current state-of-the-art climate models. There are perhaps a dozen state-of-the-art models worldwide as developed and maintained by large groups of scientists. These models are extensively evaluated by the IPCC Working Group I (e.g., IPCC 2001), and so their summary here can be brief. Such models serve as national or international resources that are generally available to appropriate collaborators and in some cases freely distributed from the Internet in a form suitable for use on multiple computer platforms with documentation to facilitate their use by independent scientists (e.g., the Community Climate System Model; Blackmon et al. 2000, 2001). However, meaningful use of these models still requires adequate scientific background, considerable individual commitment, and adequate computational resources. Such models have been under development for several decades by various groups and have many applications (e.g., Manabe and Stouffer 1996; Osborne et al. 2004).

Climate is modeled by simulation of the atmospheric weather and coupled surface processes on an hour-by-hour and day-by-day basis. The surface processes include an ocean model, a sea ice model, and a land surface model. The fluid behavior of the atmosphere and oceans are described by partial differential equations that are numerically integrated. The most advanced such "Earth System" models have been developed by large teams of scientists with considerable institutional support. The World Climate Research Programme of the World Meteorological Organization is largely devoted to coordination between the various modeling groups and sponsorship of multiple evaluation activities of model components and complete model simulations to improve these models.

Climate is established from the simulations of these models through various kinds of averaging in time and space and other such analyses that are commonly used with observational data or to help diagnose the functioning of the system. A variety of model outputs are produced, each of which may be of interest to a different community of scientists.

The overall strategy for use of these models to address impacts of some imposed change is relatively simple. The equations are integrated over a sufficiently long period, often many simulated years, to establish their climatology. Such a simulation is then repeated, except for the assumed change, such as land use (e.g., Maynard and Royer 2004), and the consequent climate impact and its statistical confidence level is assessed by the difference between the two states and through its comparison with natural fluctuation statistics.

The production of a sufficient number of independent samples from this naturally chaotic system is achieved by some combination of simulating for a sufficiently long period, carrying out the integrations multiple times (ensemble approach, cf. Boer 2004), and using statistical methods of pattern analysis to optimize the signal (climate change, for example) relative to the natural variability (that is, noise) of the system. Available computational resources, and more important, questions as to the correctness of model details may limit such analyses.

The latter issue is addressed and more robust conclusions are obtained by carrying out the same integration with multiple independent models and identifying and analyzing any significantly different results that arise or by assessing the model components most important for the answer being sought in terms of how they may contribute to the uncertainty of the result. The time required to equilibrate is necessarily at least as long as the longest time scales of the individual systems. For the oceans, this is determined by depth included and can be many centuries for a full ocean. For prescribed vegetation and soil properties (that is, fixed soil carbon and nitrogen), soil moisture takes longest to equilibrate. Models that include the development of forests or some of the slower soil processes may also require centuries. Large ice sheets may require millennia.

4.3.1.2 Model Components Most Closely Connected to Biophysical Impacts of Land Use Change

Land surface models couple atmospheric processes with the conservation of energy and water, which may depend on land cover. These models initially simply tracked reservoirs of water whose temperature was adjusted to conserve energy by turbulent exchanges with the atmosphere (e.g., Manabe et al. 1965; Manabe and Bryan 1969; Manabe and Wetherald 1975). Later authors (e.g., Dickinson et al. 1981; Dickinson 1984; Sellers et al. 1986) addressed the need to include land cover elements that varied geographically and included greater complexity, such as a vegetation component and multiple temperature and soil water variables.

The largest modifications in simulations from those of earlier efforts resulted from the stomatal controls in plants on transpiration. This aspect is now modeled from carbon assimilation. Its inclusion (e.g., Sellers et al. 1997) and that of snow cover and micrometeorology is now relatively advanced and well understood, but implementations may differ in details because of different objectives and institutional histories (e.g., Dai et al. 2003). Improvements in the mapping of different land covers and their correlations with leaf area and albedo are being implemented with use of new global remote sensing data (e.g., Buermann et al. 2002; Tian et al. 2004a, 2004b). Many of the more important impacts of land use/land cover change, such as impacts on the hydrological cycle, require not only these components but also the coupling of the surface micrometeorology to atmospheric boundary layer processes.

What attributes of land use changes need to be incorporated in climate models? The answer to this question entails all key attributes that current climate models use as inputs when calculating energy fluxes. These include the LAI and hydraulic properties mentioned earlier, albedo and surface roughness, stomatal functioning as an element of evapotranspiration and carbon cycling, and the ways energy fluxes might be changed independent of the above—for example, through nutrient changes. These properties are included either from prescribed vegetation cover with seasonal phenologies or through models of the vegetation dynamics.

It is currently not practical to include a wide variety of plant species, so that the climate role of vegetation is represented by 10–20 "plant functional types" (e.g., Bonan et al. 2002). The extra detail of subtle species-differences within the same functional group may never yield sufficient additional predictive power to make species-specific models desirable. The dynamics of vegetation as it interacts with soil moisture and its climatic environment can be formulated at various levels depending on the time scales involved. For changes over a few years or less, only leaf properties need to be included. On longer time scales, growth, competition, and hence initiation and survival of individual plant types may have to be included to characterize the terrestrial feedbacks adequately.

In general, the vegetation cover can have strong influences on the surface exchanges of energy and water. Past sensitivity studies (e.g., Bonan et al. 1992; Foley et al. 1994) have revealed that a transition from systems shaded by trees to short vegetation covered by snow can have a large positive feedback on climate in high latitudes. Raupach (1998) has shown these sorts of response to gradual temperature changes are not always incremental but can instead involve abrupt transitions or thresholds. In addition, spatial scales of surface heterogeneity in terms of wind, soils (e.g., Zender and Newman 2003), soil moisture, and vegetation will interact with the underlying turbulent convection to structure its spatial scale and consequently the probability and amounts of precipitation.

4.3.1.3 Examples of Land Use Change Addressed in Past Literature

Various idealized scenarios have been studied. One popular question has been the possible impacts of complete conversion of the Amazon forest to degraded pasture (e.g. Dickinson and Henderson-Sellers 1988; Lean and Warrilow 1989; Shukla et al. 1990; Nobre et al. 1991; Zhang et al. 1996; Voldoire and Royer 2004). Early analyses of this extreme scenario differed fairly widely not only in results but also in how the scenario was translated into model parameters. The controlling parameters are the surface albedo, surface roughness, soil hydrological properties, and possibly the capacity of the vegetation to transpire through stomatal functioning.

The most obvious changes when the Amazon forest is converted to pasture are that its albedo increases and it becomes a much smoother surface. The increased albedo reduces surface sensible and latent fluxes and ultimately alters precipitation in almost all models; the decreased surface roughness tends to make the surface warmer, and the increased upward infrared radiation leads to further reduction of boundary layer buoyancy generation. Substantial feedbacks occur with atmospheric cloud cover, with less precipitation being accompanied by less cloud cover and more surface solar heating. The need for more realistic scenarios that address the consequences of conversion of smaller areas and forest fragmentation is recognized but has not yet been adequately addressed.

A few studies have addressed conversions in the United States between forest and cropland (e.g., Bonan1999; Pan et al. 1999; DeFries et al. 2002a). Although such conversions superficially appear similar to Amazon deforestation, results have been remarkably different, and, in particular, the surface temperatures for cropland have declined rather than increased. This effect appears to be a result of increases in evaporative cooling and suggests that plant nutrition effects, especially nitrogen levels, may provide strong coupling to surface temperatures and precipitation.

4.3.1.4 Models of Biogeochemical Impacts of Land Cover Change on Climate

Biogeochemical models to estimate greenhouse gas emissions from land cover change are much simpler than the climate models used to estimate the biophysical impacts. Most efforts have focused on the release and uptake of atmospheric carbon dioxide from land cover change, particularly deforestation. The most widely used approach is a "bookkeeping" model, in which estimates of the areas of each type of land use change are combined with prescribed response curves for decay and regrowth (Fearnside 2000; Houghton and Hackler 2001).

The land use changes in the bookkeeping model include the conversion of natural ecosystems to croplands and pastures, the abandonment of agricultural lands with subsequent recovery of natural vegetation, shifting cultivation, harvest of wood (forestry), plantation establishment, and, in some instances, fire management (exclusion and suppression of fire). The bookkeeping approach requires three basic inputs: rates of clearing, biomass at time of initial clearing, and decay and regrowth rates following clearing. Houghton and Hackler (2001) have applied the model at a very coarse, continental scale. More recently, remote sensing analysis to determine rates of deforestation have been combined with the bookkeeping model for more spatially explicit estimates of carbon emissions (Achard et al. 2002; DeFries et al. 2002b).

In addition to the bookkeeping approach, process models of the terrestrial carbon cycle have been used to estimate carbon fluxes from land use change (DeFries et al. 1999; McGuire et al. 2001). Such models simulate carbon stocks in vegetation and soil and the uptake and release of carbon through photosynthesis and respiration, based on variables such as climate, incoming solar radiation, and soil type. The most recent developments are dynamic models that simulate the response of vegetation to climate change and enhanced growth from elevated atmospheric carbon dioxide concentrations, as well as the resulting feedbacks to the atmosphere through changes in the vegetation's uptake and release of carbon dioxide (Cox et al. 2000). Anthropogenic land cover changes have not yet been incorporated in this framework.

Most efforts to model greenhouse gas emissions from land cover change have focused on carbon dioxide. Models to estimate emissions of other greenhouse gases from land use change, including methane from landfills, rice paddies, and cattle, and nitrous oxide from agricultural soils, are hampered by incomplete understanding of the biological processes.

4.3.2 Critical Evaluation of Approaches

4.3.2.1 Modeling of Biophysical Impacts of Land Cover Change

This section assesses how successful we judge models to be in attempting to model the impacts of land cover change on local climates. The local and regional climate variables that are modeled are primarily surface temperature and humidity and rainfall. We address how well this is done from the viewpoint of somebody who might want to use these models as a tool. A description of the details of any one model is far too complex to be presented here. Rather, in order to assess their success, we describe in broad-brush terms what the models are trying to do. Details are omitted, such as the fact that surface temperature is not a single variable but has several important elements that must be individually modeled. The type of rainfall believed to be most affected by land use change is of the "convective" (thunderstorm) variety. Because it involves important processes that occur on scales that are not incorporated in current models, we judge that changes of this variable are not yet reliably modeled.

4.3.2.1.1 Modeling of temperature change

Current modeling can be judged to provide, in principle, adequate results for temperature changes on a large scale.

Temperatures change with land cover change because of changes in absorbed solar radiation (controlled by cloud cover and albedo), because of changes in the fraction of energy going into evapotranspiration, and because of changes in roughness elements alter turbulence patterns. The land surface modeling of these relationships is limited primarily by uncertainties as to how albedo, roughness elements, clouds, and precipitation will change with land use change. Mathews et al. (2004) estimate that past land cover change has cooled the world by between 0.1 and 0.2 K and that the carbon released by this land cover change has warmed the world by a comparable amount.

4.3.2.1.2 Representation of heterogeneous land surface in models

Land cover is heterogeneous on a spatial scale that is much finer than the coarse grid cell size of climate models; these models treat all vegetation within grids the size of many thousands of square kilometers as essentially homogeneous. Because the resolution is so coarse, it is not possible to simulate with confidence the possible effects of forest fragmentation and inclusion of patches of other cover, such as crops or pasture. Local micrometeorological factors that will change with land cover exert considerable controls on local and regional temperatures. Since such changes are confined to the fraction of land whose use/cover has been changed and can go in both directions, their contribution to global temperature changes is usually thought to be relatively small. However, they can become considerably more significant if temperature changes are weighted by various risk factors such as proximity to human populations. The micrometeorological effects for particular local or regional systems may have important consequences for precipitation, as discussed later, but we do not understand how to include such effects in climate models.

4.3.2.1.3 Difficulties in modeling rainfall

Modification of rainfall is potentially one of the most important climatic impacts of land use change (e.g., Pielke 2001). This interesting issue is not well developed because it involves scaling aspects of modeling that are not sufficiently advanced. However, it is possible to clarify what is most important. Precipitation in summertime and tropical systems (that is, rainfall) is largely or entirely convective. It is this type of precipitation that is most sensitive to the atmosphere's lower boundary and hence land use change. Wintertime precipitation is largely generated by large-scale storm systems that are less connected to the surface and often originate over the ocean.

Convective rainfall is initiated primarily because of the instability (positive buoyancy) of near surface air that acts in two ways: it allows convective plumes to penetrate from the boundary layer up to the level of free convection, where moist instability carries it further, as high as the top of the tropopause; and through horizontal gradients it creates pressure forces that drive horizontal convergence, hence further uplift. The drivers of these mechanisms are land heterogeneities, which are currently lost in the processes used to scale the effects of motions on these scales to the scales resolved by climate models. In principle, scaling should include all the statistical properties given by distributions of the small-scale systems that couple back to the large scale. However, the formulations currently used assume an underlying homogeneous surface and may be intrinsically incapable of determining the changes of rainfall from land use change.

4.3.2.1.4 Difficulties assessing the significance of modeled impacts of land use change

Modeling studies test the sensitivity of climate to land cover changes by varying only the land cover in the model. In reality, land cover is only one of many factors that determine climate, including winds, incoming radiation, and clouds. These confounding factors make it difficult to identify a ''land cover signal'' from natural variability either in a model or in observations. Although sound statistical procedures are available for determining the ''signal to noise'' ratio of systems with spatially and temporally correlated randomness (e.g., Von Storch and Zwiers 1999), these have commonly not been used in studies of climate change from land use change. This limitation hampers interpretation of impacts reported in the literature.

4.3.2.1.5 Other complexity issues related to inadequacies of scaling methodology

More detailed models traditionally calculate evapotranspiration in terms of three components: transpiration, soil evaporation, and canopy evaporation (interception loss). Model results depend on how these are apportioned, which depends strongly on precipitation intensities. One difficulty with many models is that they apply their calculated precipitation and radiation from the atmospheric model uniformly over their grid-squares. These resolution elements are generally of much larger scale than the occurrence of individual convective systems, however, and hence poorly match actual local precipitation intensities and radiation. Appropriate precipitation and radiation downscaling must be used in the model to obtain better results. Because of the use of faulty satellite-derived data, some models have underestimated the LAI of tropical forests and in doing so have exaggerated the losses of soil water to bare soil evaporation.

Current parameterizations of runoff do not provide very plausible schemes for the downscaling to the scales on which precipitation and runoff occur. Because runoff provides a major feedback on soil moisture, inadequacies in its treatment introduce uncertainty into the issue of soil-moisture/vegetation interaction (e.g., Koster and Milly 1997).

4.3.2.2 Modeling of Biogeochemical Impacts of Land Cover Change

Model estimates of greenhouse gas fluxes from land cover change have a large range of uncertainty. Carbon dioxide emissions from deforestation and uptake from regrowth are the most uncertain components of the global carbon budget reported by the IPCC. The uncertainties arise from imprecise data on the required model inputs. Estimates of the rates of deforestation vary, and spatially explicit data covering the entire tropical belt are not available. These estimates are improving with the use of satellite data, but there is currently no pan-tropical observational system for monitoring deforestation. A second source of uncertainty arises from lack of spatial data on biomass distributions prior to clearing. Field measurements of biomass are based on point-samples, which are difficult to extrapolate over larger areas. Satellite capabilities to assess biomass distributions over large areas are not in place.

Estimates of other greenhouse gas fluxes—methane and nitrous oxide—from land cover change are even more uncertain than estimates of carbon dioxide fluxes. For these gases, inadequate understanding of the biological processes limits the modeling capabilities.

4.3.3 Research Needs

Future scenarios need to provide data quantified for input to climate models. Specifically, they need to describe in quantitative terms how the surface structure and its radiative properties have been modified, using parameters used by the climate models.

Test cases are needed with simultaneous observations of land use change and climate change to test modeling predictions; some areas expected to undergo large land use change in the future should be equipped with an adequate observational system to measure the consequent climate change.

An interactive vegetation-climate dynamical system needs to be a component of future scenarios. That is, quantitative trajectories of land use on a global basis should be prescribed in terms of quantities that can be used as boundary conditions for climate models. In this way, it would become possible to address the synergies between land use-driven climate change and greenhouse warming.

For the biogeochemical fluxes, improved monitoring systems for deforestation and biomass distributions are needed to reduce uncertainties of carbon emitted to the atmosphere as a result of land cover change. In addition, dynamic models that estimate changes in carbon fluxes as a result of vegetation being altered by climate change need to also include vegetation changes expected because of human activities, which will also be altering the landscape.

4.4 Forecasting Change in Food Demand and Supply

Over the past 50 years, there have been at least 30 quantitative projections of global food prospects (supply and demand balances), as well as numerous qualitative predictions, with the latter often tied to short-term spikes in global food prices. Global simulation models that simulate the interrelationships among population growth, food demand, natural resource degradation, and food supply are yet another class of forecasting exercises (Meadows et al. 1972, 1992; Mesarovic and Pestel 1974; Herrera 1976); but they are not commonly used today.

The number of players engaging in projections of future food demand, supply, and related variables at the global level has been declining over time. Important organizations conducting projections on the global scale include the Food and Agriculture Organization of the United Nations, the Food and Agriculture Policy Research Institute, the International Food Policy Research Institute, the Organisation for Economic Co-operation and Development, and the U.S. Department of Agriculture. Other food projection exercises focus on particular regions, like the European Union. Finally, many individual analyses and projections are carried out at the national level by agriculture departments and national-level agricultural research institutions. Results from some of these models are published periodically with updated projections. In addition to their differing coverage and regional focus, existing approaches also vary in the length of the projections period, the approach to modeling, and in the primary assumptions made in each model. The focus in this section will be on global food projection models.

4.4.1 Existing Approaches

This section examines the evolution of food supply and demand projections and examines current food projection models based on various criteria, following McCalla and Revoredo (2001), who carried out a critical review of food projection models.

4.4.1.1 Evolution of Food Supply and Demand Projections

Early food models (for example, the mathematical model of population growth posited by Thomas R. Malthus) focused on potential food gaps by comparing fixed land resources with rates of growth of population. This was followed by a requirements approach, where minimum nutritional needs were multiplied by population to produce projected food needs; on the supply side, yield increases were added to supply projections.

By the 1960s, income and Engel curves (statistical relationship between consumption and income) were added to food demand projections, while Green Revolution changes in food production, as well as resource limits, were added on the supply side. Food price instabilities in the early 1970s, making the assumption of constant prices illusionary, spurred the disaggregation of global models to the national level, with domestic supply and demand, country by country, and appropriate cross-commodity (maize and wheat, for instance) relationships embedded and with explicit recognition of policy built in. Disaggregation also allowed for a more detailed representation of changes in food preferences, including the diversification of diets with changing income levels. Models thus graduated from supply-and-demand gap projections into global price equilibrium trade models, which are more sophisticated, much larger, and more expensive to maintain (McCalla and Revoredo 2001).

4.4.1.2 Approach to Food Projections Modeling

The main types of global food projection models fall into two categories, trend projection models and world trade models.

Trend projection models project supply and demand separately based on historical trends. Relative prices are assumed to be constant over time. In pure trend projection models, which include most of the existing trend models, the difference between projected consumption and projected production creates a gap, indicating food surpluses and shortages at the regional or global level, which can be bridged through trade. FAO's projections during the 1960s to the 1980s, IFPRI's 1977 and 1986 projections (IFPRI 1977; Paulino 1986), OECD's 1960s projections, and USDA's 1960s projections fall into this category. In extended trend projection models, a spatial trade model is used to distribute the projected surpluses or deficits among regions and countries (Blakeslee et al. 1973). This can be done in the form of transportation models, which minimize the cost of moving surpluses to shortage locations by estimating food flows over geographical regions.

The simplest world trade models assume a global supply and demand equilibrium. In particular, these models estimate supply and demand functions at the country/regional levels; projections are aggregated at the world market, where prices adjust until global supply equals global demand. These models are also called price endogenous models. All major food projection models in use fall into the class of global non-spatial trade models. They include the different versions of FAO's World Food Model (FAO 1993), partly used in FAO's *World Agriculture: Towards 2015/30* study (Bruinsma 2003), IFPRI's IMPACT model (Rosegrant et al. 2001), FAPRI's commodity models (Meyers et al. 1986), the World Agricultural Model from the International Institute for Applied Systems Analysis (Parikh and Rabar 1981), the Free University of Amsterdam's Model of International Relations in Agriculture (Linnemann et al. 1979), and the World Bank model (Mitchell et al. 1997).

An alternative form of world trade models starts by assuming the costs of trade among regions have been minimized (using output from transportation models), subject to constraints that represent the characteristics of the different regions (Thompson 1981). These models depict spatially varying patterns of trade between different regions. Unfortunately, spatial models do not predict trade flows well, due to the reality of quantitative trade barriers, the heterogeneity of commodities in terms of characteristics and seasonality, and risk diversification strategies being pursued by importers (McCalla and Revoredo 2001).

Earlier models used linear equations, while more recent versions are based on nonlinear elasticity equations, which can better handle sharp perturbations (or "shocks"). Early projection models were static, with point estimates for future years dependent on projected rates of change in population and other key variables. The alternative approach entails recursive models that estimate all variables annually, moving repeatedly toward the final year, allowing for the observation of the path of adjustment. Most projection models are partial equilibrium models—that is, they focus on the agricultural sector instead of representing the entire economy.

4.4.1.3 Coverage

Country and commodity coverage differ by model. Whereas some models explicitly focus on developing countries (for example, the IMPACT and FAO models) and therefore tend to aggregate industrial countries and regions, others have been specifically developed to analyze the food supply, demand, and trade projections of industrial countries, in general, or the European Union, in particular, like CAPRI of Bonn University (CAPRI 2004).

The European Commission, for example, recently commissioned a study on the impact of its Mid-Term Review proposals for the year 2009 with reference to a status quo policy situation, involving six different agricultural projection models: the EU-15 agricultural markets model and the ESIM model, both under the Directorate General for Agriculture of the EU (DG-AGRI 2003a); the FAPRI model (FAPRI 2002a, 2002b); the CAPRI model of the University of Bonn, operating at the regional level (DG-AGRI 2003b); the CAPMAT model of the Centre for World Food Studies of the University of Amsterdam and the Netherlands Bureau for Economic Policy Analysis in The Hague (DG-AGRI 2003a); and the CAPSIM model, operating at the national level, also from the University of Bonn (DG-AGRI 2003a, 2003c). Similarly, commodity coverage differs among models, depending on the region or issue of concern. IMPACT, for example, started out with a focus on rice, followed by other staple crops of importance to the food security situation of poor countries, before adding higher-value commodities.

4.4.1.4 Projections Period

Long-term projections include those by IFPRI and FAO (as presented in *World Agriculture: Towards 2015/30*). Short-term projections have been developed by FAO, FAPRI, USDA, and OECD.

FAO has produced a series of long-term projections, beginning with the *Indicative World Plan for Agricultural Development* (FAO 1970), followed by *World Agriculture: Towards 2000* (Alexandratos 1988), *World Agriculture: Towards 2010* (Alexandratos 1995), and *World Agriculture: Towards 2015/2030* (Bruinsma 2003). These are recursive global non-spatial trade models. The most recent study has a base year of 1997–99, incorporates the medium-variant U.N. population projections (2001), GDP data from the World Bank, and agricultural data from its own databases to project food supply, demand, and net trade for crops and livestock products for 2015 and 2030.

FAO develops projections through many iterations and adjustments in key variables based on extensive consultations with experts in different fields, particularly during analysis of the scope for production growth and trade. The end product may be described as a set of projections that meet conditions of accounting consistency and to a large extent respect constraints and views expressed by the specialists in the different disciplines and countries (Bruinsma 2003, p. 379). The FAO study only uses one scenario: a baseline that projects the future that the authors anticipate to be most likely.

The International Model for Policy Analysis of Agricultural Commodities and Trade was developed at IFPRI in the early 1990s (Rosegrant et al. 1995). IMPACT is a representation of a competitive world agricultural market for 32 crop and livestock commodities and is specified as a set of

43 country or regional sub-models; supply, demand, and prices for agricultural commodities are determined within each of these. World agricultural commodity prices are determined annually at levels that clear international markets.

IMPACT generates annual projections for crop area, yield, and production; demand for food, feed, and other uses; crop prices and trade; and livestock numbers, yield, production, demand, prices, and trade. The current base year is 1997 (average of 1996–98). The model uses FAOSTAT agricultural data (FAO 2000); income and population data and projections from the World Bank (World Bank 1998, 2000) and the United Nations (UN 1998); a system of supply and demand elasticities from literature reviews and expert estimates; rates of malnutrition from the U.N. Administrative Committee on Coordination–Subcommittee on Nutrition (ACC/SCN 1996) and the World Health Organization (WHO 1997); and calorie-malnutrition relationships developed by Smith and Haddad (2000).

The Food and Agricultural Policy Research Institute publishes short-term projections of the U.S. as well as an annual world agricultural outlook (FAPRI 2003). This consists of an integrated set of non-spatial partial equilibrium models for major agricultural markets, including world markets for cereals, oilseeds, meats, dairy products, cotton, and sugar. For each commodity, the largest exporting and importing countries are treated separately, with other countries included in regional groupings or a "rest of world" aggregate. For most countries and commodities, the model estimates production, consumption, and trade; in many cases the model also estimates domestic market prices, stocks, and other variables of interest. Parameters are estimated based on econometric techniques, expert opinions, or a synthesis of the literature. Similar to IFPRI's IMPACT model, area is generally a function of output and input prices and government policies, while yield equations incorporate technical progress and price responses. The projection horizon is 10 years (DG-AGRI 2003a).

The OECD *Agricultural Outlook* provides a short-term assessment (five years ahead) of prospects for the markets of the major temperate-zone agricultural products of OECD members (OECD 2003). The projections to 2008, presented in the latest *Outlook* based on the recursive AGLINK model, are considered a plausible medium-term future for the markets of key commodities. Projections are developed by the OECD Secretariat together with experts in individual countries from annual questionnaires supplemented with data from FAO, the United Nations, the World Bank, and the IMF to determine market developments in the non-OECD area. National market projections are then developed with AGLINK and linked with one another through trade in agricultural products. Final results are presented following a series of meetings of the various commodity groups (cereals, animal feeds and sugar, meat and dairy products) of the OECD Committee for Agriculture (Uebayashi 2004).

The U.S. Department of Agriculture also produces short-term baseline projections of the agricultural situation 12 years into the future (USDA 2003). These projections cover agricultural commodities, trade, and other indicators, including farm income and food prices. The USDA presents a baseline scenario that projects a future with no shocks, a continuation of U.S. policies, and other specific assumptions related to agricultural policies, the macro economy, weather, and international development. Crops included are corn, sorghum, barley, oats, wheat, rice, upland cotton, and soybeans, as well as some fruit, vegetable, and greenhouse/nursery products. The model also produces projections for livestock, including beef, poultry, and pork. The projections that are presented tend to focus on the situation in the United States.

4.4.2 Critical Evaluation of Approaches

In their assessment of global projection models, McCalla and Revoredo (2001 p. 39) conclude that projections with shorter time horizons are more accurate than those with longer horizons; that projections are more accurate for aggregations of components—regions, commodities—than for the component parts themselves; and that projections for larger countries tend to be more accurate than for smaller ones. Data problems are a major cause of error, especially in developing countries. Moreover, data deficiencies are most frequently encountered in countries with severe food security problems, leading to erroneous conclusions and making it particularly difficult to develop adequate policy interventions.

For industrial countries, modeling rapidly changing, complex domestic policies, including quantitative border restrictions, is a major issue of concern. Rosegrant and Meijer (2001) point out that for IMPACT, the main discrepancies in the projections are due to short-term variability, such as the collapse of the Soviet Union or major weather events, which cause large departures from fundamental production and demand trends—variability that long-term projection models are not intended to capture.

Most of the currently used projection models are equilibrium models, which by construction require continuous adjustment to produce consistent, stable conclusions (McCalla and Revoredo 2001).

Food projection models typically produce alternative scenario results, which can then be used to alert policymakers and citizens to major issues that need attention. A test for the usefulness of these models may therefore be whether the results of these models (for example, the different scenarios) enrich the policy debate (McCalla and Revoredo 2001).

While models can make important contributions at the global and regional levels, food insecurity will be increasingly concentrated in individual countries with high population growth, high economic dependence on agriculture, poor agricultural resources, and few alternative development opportunities. These countries continue to be overlooked in regional and global studies because, overall, resources are sufficient to meet future food demands.

Each of the models described includes several critical assumptions in their approaches. Although the general methodology and underlying supply and demand functional forms are well established in the literature and have been widely validated, the details of how to implement these principles in specific models are not agreed on. For example, the elasticity of supply and demand functions is often unknown. Moreover, the supply and demand functions must be adjusted by growing incomes or population growth, which are not easily predicted and thus introduce an exogenous layer of uncertainty.

4.4.3 Research Needs

Future research should include the integration of poverty projections with global food supply and demand projections. In addition, distributional consequences of such projections need examination. Moreover, research aimed at generating future food security–environment scenarios must sufficiently disaggregate agroecologies and commodities so that chronically food-insecure countries do not get overlooked in regional/global modeling exercises. To represent the nexus of poverty, food insecurity, and land degradation, we will need models that better treat the way changes in ecosystems influence these factors and in turn are driven by them. Last, there is clearly the possibility that new technologies, most notably genetically modified crops, could alter food production systems in ways that have implications for human well-being, local economies, and land practices. A forthcoming study by the National Research Council of the U.S. National Academy of Sciences is focusing on alternative futures due to biotechnology, and that study could be a foundation for better models of food production.

4.5 Forecasting Changes in Biodiversity and Extinction

Forecasting changes in biodiversity is key to developing plausible scenarios of the future. Unfortunately, biodiversity does not mean the same thing to all ecologists and cannot be assigned one unambiguous metric. For practical reasons, the MA scenarios focus on species richness. Changes in species richness include both gains and losses of species. This section briefly outlines several approaches to predicting changes in species richness on the time scale of 100 to 1,000 years. Global extinction is considered by some to be the most serious of all the anthropogenic global changes because it is the only one that will never be reversed.

4.5.1 Existing Approaches

4.5.1.1 Qualitative Approach

One of the earliest attempts to develop global biodiversity scenarios used a qualitative approach (Sala et al. 2000; Chapin III et al. 2001). The exercise focused on terrestrial biomes and freshwater ecosystems, but the qualitative approach could be used similarly to evaluate patterns of biodiversity change in the oceans. The globe was divided into 11 biomes and two types of freshwater ecosystems, and scenarios were developed for the year 2100. The first step was to identify, based on expert opinion, the major drivers of global biodiversity change. The major drivers were determined to be changes in land use, climate, nitrogen deposition, biotic exchange, and atmospheric concentration of carbon dioxide. Biotic exchange referred to the accidental or deliberate introduction of non-native species into an ecosystem.

The second step broke the analysis into two components: assessing the drivers of biodiversity change and characterizing biome-specific sensitivity to changes in those drivers. Patterns of change for drivers were described from a series of existent models. For example, the IMAGE 2 model (Alcamo 1994) provided patterns of global land use change, and Biome 3 (Haxeltine and Prentice 1996) yielded estimates of climate change and potential vegetation. More qualitative models were used to estimate the global patterns of the other drivers. Drivers were not expected to change uniformly across biomes. Although there was agreement that biomes ought to react differently to changes in drivers, there was no quantitative assessment of biome sensitivity to each driver. Instead, the exercise developed a ranking of sensitivity for each driver and biome based on the opinion of experts representing each biome. These experts have all worked in the biome that they were representing; their appreciations of biome sensitivity were based on their understanding of the ecology of each biome and were calibrated across biomes at a workshop at the National Center for Ecological Analysis and Synthesis, University of California, Santa Barbara. Sensitivity estimates were ranked on a scale from 1 to 5.

The relative expected change in biodiversity from each biome and freshwater ecosystem resulting from each driver was calculated as the product of the expected change in the driver and the biome sensitivity. Finally, the total biodiversity change per biome depended on the interactions among drivers of biodiversity change. The exercise developed three alternative scenarios by assuming that there were no interactions among drivers, that the interactions were synergistic, or that the interactions were antagonistic. The three scenarios would encompass a range of potential outcomes. Information was not available to assign a higher probability for any of the alternatives. Computationally, the no-interaction scenario calculated total biodiversity change as the sum of the effects of each driver, the synergistic scenario used the product of the change resulting from each driver, and the antagonistic scenario used the change resulting from the single most influential driver.

4.5.1.2 Correlation to Environmental Variables

Climate has been identified as one of the most important correlates of species richness for a wide range of taxa (Rosenzweig 1995; Whittaker et al. 2001; Brown 2001). In combination with changing topography, climate change has been invoked to explain speciation and extinction events in such diverse taxa as hominids (Foley 1994), trees (Ricklefs et al. 1999), carabid beetles (Ashworth 1996), and birds (Rahbek and Graves 2001). Research on elevational clines in species richness (e.g., Rosenzweig 1995; Lomolino 2001; Brown 2001) further supports a fundamental role for climate as a determinant of patterns of biodiversity.

Many species exhibit a latitudinal gradient in species richness (e.g., Turpie and Crowe 1994; Cumming 2000) that is strongly linked to climate (Gaston 2000; Whittaker et al. 2001), available energy, and primary production (e.g., O'Brien 1998). These gradients have been used as one way of predicting species richness over large areas, based on the correlation between species occurrences and environmental conditions. Correlative approaches typically use general linear models to estimate species richness in unsampled areas. Species richness is frequently considered as a response variable in its own right. An alternative but more time-consuming approach is to model individual species occurrences and then to stack species models to produce estimates of species richness.

A special class of "correlative models" that has been used to predict biodiversity impacts is the so-called bioclimatic envelope approach (Midgley et al. 2002; Erasmus et al. 2002). These models identify the current distribution of species in terms of climatic and other environmental variables (topography, soils, etc.) and then infer local disappearance of species because new conditions are outside the species "bioclimatic envelope." This approach cannot really predict whether a species will become extinct; instead, it predicts changes in where species should occur. If no appropriate climate zone exists, then it might be concluded that a species will go extinct, but this is not certain.

4.5.1.3 Species-Area Relationship

The most widely used approach for predicting species loss entails the application of the species-area relationship (Pimm et al. 1995; May et al. 1995; Reid 1992). This describes one of the most general patterns in ecology (Rosenzweig 1995; Brown and Lomolino 1998; Begon et al. 1998): the relationship between the area of sampling and the number of species in the sample follows the power law,

$$S = cA^z$$

where S is the number of species, A is the sampled area, z is a constant that typically depends on the type of sampling, and c is a constant that typically depends on the region and taxa sampled. This was the approach adopted for the terrestrial biodiversity scenarios, and its assumptions and uncertainties are discussed at length in Chapter 10. Here we simply revisit the high and low points of this approach.

The idea behind using the SAR to estimate extinction rates is relatively straightforward; it simply assumes that the number of species remaining after native habitat loss follows a species-area curve, where A is the area of native habitat left. A typical value of z for islands of an oceanic archipelago or other types of habitat isolates (mountaintops, forest fragments, etc.) is 0.3 (Rosenzweig 1995). It takes from a few decades to several centuries for the species number in the remnant habitat to reach the equilibrium predicted by the SAR (Brooks et al. 1999; Ferraz et al. 2003; Leach and Givnish 1996; see also Chapter 10). If habitat restoration takes place during this time, the extinctions will be fewer than predicted by the SAR.

4.5.1.4 Threat Analyses Approaches

In many cases species are at risk because of habitat degradation and environmental threats that do not lend themselves easily to a strict species-area curve approach. This is especially true for freshwater and marine biodiversity. In freshwater systems, water withdrawals and dewatering of streams obviously can make it impossible for fish to survive. One approach is to link water discharge to fish diversity (e.g., Oberdorff et al. 1995). Similarly, in the marine environment extinctions are very hard to observe, and the primary impact that has actually been measured is a change in the biomass occupying different trophic levels. Chapter 10 presents a method for relating changes in biomass at trophic levels to changes in biodiversity. These threat analyses approaches typically start with a statistical relationship between some measured stress and a measured response in a particular taxa (like fish in response to reduced water discharge).

4.5.1.5 Population Viability Analyses

In order to categorize species according to their risk of extinction, modelers routinely conduct population viability analyses. These range from simple diffusion approximations for population fluctuations to detailed stochastic demographic matrix models. In all cases extinction is primarily a function of the current population size, environmental variability, and rate of population growth rate (Morris and Doak 2002). Changes in extinction risk will result if any of these key factors is altered. To date, most models that attempt to predict changing extinction risk per species tend to focus on what happens because species abundance is reduced. There is no reason, however, that changes in environmental variability (which is expected to be affected by climate change) could not be used to project an altered extinction risk for any given species. In theory, someone could sum PVA models over many species and then generate predictions about aggregate extinction risks.

4.5.2 Critical Evaluation of Approaches

4.5.2.1 Qualitative Approach

The strengths of the qualitative approach are that it is simple, tractable, and easy to communicate. It made global biodiversity scenarios possible before global species richness was fully described. The major weaknesses of the approach are associated with its scale and qualitative nature. The scale at which the qualitative biodiversity scenarios were run was very coarse, with only 11 terrestrial units and two freshwater ecosystem types. The coarse scale resulted in large errors in driver patterns and also yielded results at a scale that was too coarse to be used in management and decision-making. Most decisions about biodiversity occur at finer scales—from paddocks to nations—and never reach the level of biomes. The second weakness is the qualitative nature of the exercise that is related with the scale. This type of exercise may only be doable at a coarse scale, where differences among biomes are large enough to be captured without more sophisticated calculations.

4.5.2.2 Correlation to Environmental Variables

In general, correlative approaches offer a reasonable alternative to mechanistic methods. Their main weaknesses are the same as those of any statistical analysis. The results may be influenced by biases in sampling regime, they rely on large sample sizes for accurate prediction, and they may fail to take adequate account of complex system dynamics and nonlinearity. Correlative approaches also make the assumption that species will occur wherever habitat is favorable, ignoring the potential for dispersal limitation and other confounding biotic interactions (such as competition and predation) unless they are explicitly included in the model.

Ideally, linear models of species richness should be based on a small number of variables with well-demonstrated relevance to the occurrence of the study taxon. A number of studies have reported poor out-of-sample prediction, which can often result from over fitting; a variety of statistical methods (bootstrapping, jack-knifing, and model averaging) can be used to overcome this problem (Raftery et al. 1997; Fielding and Bell 1997; Hoeting et al. 1999). Several authors have used the predictive power of correlative methods to consider the likely implications of climate change for species distributions and population processes (e.g., Schwartz et al. 2001; Thomas et al. 2001; Kerr 2001; Peterson et al. 2001), although a failure to take account of covariance between climatic variables may result in oversimplification of the problem (Rogers and Randolph 2000).

A further weakness in correlative approaches is that species will not exploit their full potential geographic range if individuals are unable to reach areas where the habitat is suitable. Island biogeography (MacArthur and Wilson 1967; Hubbell 2001) has been a widely used framework for thinking about changes in species distributions. Recent studies of invasive species (e.g., Parker et al. 1999) also shed light on the dispersal ability of organisms and the ways in which physical and biological variables interact to change the extents of species ranges.

4.5.2.3 Species-Area Relationship

One strength of the SAR approach is its simplicity: it is very straightforward way to explain how the calculation of biodiversity loss is made. Furthermore, the SAR is an ubiquitous pattern in nature, with more than 150 studies documenting SARs for different taxa and regions (see, e.g., the review in Lomolino and Weiser 2001). One weakness of the SAR approach is that it does not distinguish among species and hence does not tell us where to direct conservation efforts. Second, it does not predict when the loss of ecosystem services associated with a species or a group of species is going to occur, which may be before a species is locally extirpated or may not occur even after that event. Finally, the SAR approach accounts only for the impacts of habitat loss. While habitat loss is the major driver of biodiversity loss (Sala et al. 2000; Hilton-Taylor 2000), other drivers such as hunting, trade, invasive species, and climate change are also important. Nevertheless, in the case of climate change the SAR has been used to predict biodiversity loss based on predictions of habitat loss induced by climate (Thomas et al. 2004).

A major assumption of the SAR approach is that no species survive outside native habitat. Put another way, instead of stating that habitat is lost, it is more accurate to say that habitat is changed. The actual changes in habitat, even if from a forest to a plantation, do not correspond to total habitat degradation. Some species will remain, even as habitat is altered. In Costa Rica, for instance, about 20% of the bird species are exclusively associated with human-altered habitats, and the majority of species (about 66%) use both natural and human-altered habitats (Pereira et al. 2004). Furthermore, when the SAR is applied to a given region, it will project only regional extirpations. Global extinctions will depend on how many of the species going extinct are endemic to the region being considered. (See Chapter 10 for a thorough discussion of this issue.) Also, the SAR approach applies only to the native species of a region.

One large uncertainty associated with the SAR projections of biodiversity loss is the choice of the z-value (see Equation above). SARs can be classified according to the type of sampling in three categories: continental, where nested areas are sampled within a biogeographic unit, and typical z-values are in the range 0.12–0.18 (Rosenzweig 1995, but see Crawley and Harral 2001); island, where islands of an archipelago or habitat islands such as forest patches are sampled, and typical z-values are in the range 0.25–0.35 (MacArthur and Wilson 1967; Rosenzweig 1995); and inter-province, where areas belonging to different biogeographic provinces are sampled, and z-values cluster around 1 (Rosenzweig 1995). A review of the literature of SARs in vascular plants (see Chapter 10) suggests that typical intervals for the z-values can be even wider, and the mean values may differ from the ranges discussed above. It has been standard practice to use z-values of island SARs to estimate biodiversity loss (Pimm et al. 1995; May et al. 1995; Reid 1992), but arguments could be made for using the z-values of the continental or even the inter-province SARs, depending on the time scale of interest (Rosenzweig 2001).

4.5.2.4 Threat Analyses Approaches

Models that link threats like reduced water discharge to reduced diversity are in some sense a special class of correlative models, and hence have the same weaknesses as described for correlative approaches. This is a very new branch of modeling, and it is plagued by highly norepresentative taxonomic treatments. For instance, predictions of freshwater extinctions or changes in diversity are made only for fish. With the exception of coral reefs, predictions about marine diversity are also made only for fish. In fact, the data on trophic level and biomass comes from fish landed commercially; hence the relationships are based on harvested species.

4.5.2.5 PVA Models

The biggest limitation of population viability analyses models for predicting changes in biodiversity is that they are impractical because of their huge appetite for data and species-specific analyses. PVA models are best used to examine specific species. Even when applied to single species, there is extensive debate about their value because of huge uncertainty that often leads to a probability of extinction between 0 and 1 (Ludwig 1999). In management, PVAs are used for comparing relative risks of alternative options, but they do not lend themselves so well to point estimates of any given extinction probability.

4.5.3 Research Needs

There is a need for research that examines which estimation procedures for z-values and also which z-values are most appropriate for describing biodiversity loss as a consequence of habitat loss. Retrospective studies (e.g., Pimm and Askins 1995) that analyze past extinctions associated with habitat loss as well as long-term experimental studies concerning the effect of habitat manipulations on local species extinctions are needed. Also needed are approaches to validate diversity models, which includes the generation of suitable data sets of biodiversity that are publicly available.

A generalization of the SAR to multiple habitats is needed. Recently, Tjorve (2002) and Pereira and Daily (in review) have discussed the implications for biodiversity of changing the proportion of cover of different habitats in a landscape. However, more empirical and theoretical research is needed to determine how the SAR can be extended to complex landscapes with several habitats. Open questions include: Which z values should be used for different habitats? How do we estimate species loss caused by habitat conversion for species that prefer native habitat but can also survive in the agricultural landscape?

The development of models of biodiversity change that do not conveniently fit the species-area paradigm is very much in its infancy. For aquatic systems, for example, currently available data tend to represent a highly biased taxonomic sample (such as fish, while invertebrates or aquatic plants are neglected). In most cases the threat-models are extrapolated well beyond their original data range in order to obtain global predictions. These extrapolations need scrutiny. We expect that within 10 years there could be huge advances in tools for predicting aquatic biodiversity and how it responds under different scenarios.

There will probably never be "a biodiversity model" that enables us to predict changes of species richness at all of the geographic and temporal scales or for all ecosystems and taxa. The multiscale approach of the MA was met by a combined use of different quantitative and qualitative tools for estimating the future development of biodiversity in a hierarchical approach. This approach made it possible for us to answer such diverse questions as: What will the future pattern of species diversity of known groups be and what trends are to be expected in the future? Is there any scenario for significantly reducing biodiversity loss? How well can other, easy-to-obtain abiotic data be used to make predictions about biodiversity patterns? Judgment on the most appropriate methods to use should be based on the following criteria: spatio-temporal resolution, taxa of interest and data availability, ease of application, and ability to cope with unexpected events (such as increased extinction risk due to sudden population decline).

4.6 Forecasting Changes in Phosphorus Cycling and Impacts on Water Quality

Phosphorus (P) is frequently the limiting nutrient for primary production in freshwater ecosystems (Schindler 1977) and is recognized as a critical nutrient in marine ecosystems (Van Capellen and Ingall 1994; Tyrell 1999). Excess P input causes harmful algal blooms (including blooms of toxic species) as well as excessive growth of attached algae and macrophytes. Excess plant growth can damage benthic habitats such as coral reefs. Harmful algal blooms cause deoxygenation and foul odors, fish mortality, and economic losses. Impacts on human well-being include health problems caused by toxic algae blooms and waterborne diseases, as well as loss of aquatic resources. Economic costs derive from health impacts as well as increased costs of water purification and impairment of water supply for agriculture, industry, and municipal consumption (Carpenter et al. 1998; Postel and Carpenter 1997; Smith 1998). Because of the role of P in eutrophication and water quality, it was important that the MA Scenarios Working Group considered potential future changes in P flow to freshwater and marine ecosystems.

In this section, we assess the available models for P transport to water bodies, eutrophication, and impact on ecosystem services. We discuss process-based and export-coefficient models of P transport and many types of in-lake eutrophication models, from simple empirical models to more complex ones that include recycling and biotic effects. We also briefly discuss models that include interactions of policy with water quality.

4.6.1 Existing Approaches

4.6.1.1 Phosphorus Transport Models

4.6.1.1.1 Process-based models

Before discussing phosphorus models, it is important to understand how P moves through the environment. P arrives in surface waters primarily via runoff. P runoff can be dissolved in water, which moves on the surface and in subsurface flows. More commonly, P is delivered in the form of soil particles. Most P runoff is absorbed to soil particles and moves during major storms with heavy erosion (Pionke et al.1997). Once it enters the aquatic environment, P can be released in forms available for plant growth. Measures of P availability used in terrestrial ecology tend to underestimate the amount of P that can be released after soil is eroded into aquatic ecosystems (Sharpley et al. 2002).

Process-based models simulate P transport across watersheds to surface water. They have been used for small and large watersheds, in diverse soils and topographies. Such models are often used to estimate the impacts of different types of land use and management on P transport. For example, several have been used to highlight best management practices (Sharpley et al. 2002). Some of these models are based on or use the Universal Soil Loss Equation, first developed by Wischmeier (1958).

Some, like AGNPS–Agricultural Nonpoint Pollution Source (Young et al. 1989), estimate runoff in large watersheds (up to 20,000 ha) but can be used to analyze runoff from individual fields, and the impact of specific best management practices, within the overall watershed.

Other process-based models for simulating P transport include ANSWERS–Areal Nonpoint Source Watershed Environment Response Simulation (Beasley et al. 1985), GAMES–Guelph Model for Evaluating Effects of Agricultural Management Systems on Erosion and Sedimentation (Cook et al. 1985), ARM–Agricultural Runoff Model (Donnigan et al. 1977), and EPIC–Erosion-Productivity Impact Calculator (Sharpley and Williams 1990). Recent developments include models like INCA-P, a dynamic mass-balance model that investigates transport and retention of P in the terrestrial and aquatic environments (Wade et al. 2002). These models were largely developed in order to estimate the benefit or drawback of specific land management techniques and estimated P transport at the edges of agricultural fields.

4.6.1.1.2 Export coefficient models

Export coefficient models are steady-state models used to estimate P load based on the sum of P loads from various land types in a watershed (Wade et al. 2001). These models are generally simple, empirically driven, and often not spatially explicit. The name comes from the fact that each type of land in the model has associated with it an export coefficient that is an empirically determined estimate of P runoff from that type of land. Land may be defined by soil properties, land use, land management, or some combination of factors.

A few spatially explicit export coefficient models for P have been developed, such as those developed by Soranno et al. (1996), who included distance and routing to the lake, and Gburek and Sharpley (1998), who routed export to the stream from source areas in the watershed. These models tend to be highly data-intensive and are thus limited in their applicability.

Data generally come from measurements of edge-of-field P transport and field data such as the physical and chemical properties of the soil, land use, and land management properties. Export coefficient models can be linked to a GIS to estimate a runoff over a given watershed or watershed area. They often require plentiful data for parameterization and calibration (Sharpley et al. 2002).

A few recent export coefficient models have been developed to model the impact of land use change on P transport (Wickham et al. 2002). Wickham et al. (2000) use an export coefficient model to estimate total P transport with one land use map and then again with another land use map and compare the difference between the two to understand how land use change might affect P runoff.

4.6.1.2 *Freshwater Eutrophication Models That Predict Important Ecosystem and Policy-relevant Impacts*

4.6.1.2.1 Simple empirical models

The simplest, and in many ways most widely applicable, models of eutrophication are the empirical relationships between P input, or loading, to a water body and the biomass of primary producers in that water body (Rigler and Peters 1995). We will refer to these as simple empirical models for eutrophication. The general form of SEMEs is

$$A = f(\text{P input, covariates, parameters}) + \epsilon$$

In this equation, A is a measure of algal abundance such as cell concentration, chlorophyll a concentration, or primary production; P input is expressed as a rate or annual load; covariates (if present) include variates such as lake morphometry or hydrology; and ϵ are errors with a specified probability distribution (usually normal or lognormal, with moments estimated from the data). The parameters of the function f and the distribution of ϵ are fitted by regression methods.

SEMEs have a long history in limnology. An early and frequently adopted model was introduced by Vollenweider (1968). His model predicts chlorophyll concentration from P input rate, adjusted by simple corrections for water depth and hydraulic retention time. P input has also been used to predict other biotic variates, such as biomass of consumers, in lakes (Håkanson and Peters 1995). Of particular interest to the MA, P input has been used in conjunction with N:P ratios to predict concentration of cyanobacteria, an important type of toxic algae (Smith 1983; Stow et al. 1997). Harmful algal blooms are highly variable in space and time (Hallegraeff 1993; Soranno 1997). In general, predictions of chlorophyll have lower uncertainties than predictions of the timing and spatial pattern of harmful algal blooms.

4.6.1.2.2 Recycling and biotic effects models

The wide confidence intervals around predictions of empirical models and the desire to extrapolate beyond the calibration data have prompted considerable research on more complicated models of eutrophication. Much of this work has focused on P recycling from sediments and food web processes.

P recycling from sediments can cause lakes to have higher biomass of algae than expected from typical P input–chlorophyll relationships. P recycling from sediments is caused by anoxia (which increases solubility of iron-P complexes found in sediments) or turbulent mixing of sediments into the water. P recycling due to anoxia has been modeled empirically, using its correlation with other limnological drivers (Nürnberg 1984, 1995). More mechanistic models of recycling have also been developed (Tyrrell 1999).

Under conditions of excess P input, a positive feedback can maintain a quasi-stable eutrophic state. High production of algae leads to rapid depletion of oxygen in deeper water, as decaying algae sink to the bottom. Anoxia promotes recycling of P from sediments, leading to more production of algae, thereby creating a self-sustaining feedback. A model of this phenomenon exists for lakes (Carpenter et al. 1999b; Ludwig et al. 2003), though for many applications at least one parameter of the model has a large standard deviation (Carpenter 2003). This mechanism is exacerbated by sulfate deposition caused by coal-burning industrial processes. In anoxic waters or sediments of lakes and reservoirs, sulfate reduction leads to formation of iron sulfide, decreasing the availability of iron to bind P in sediments (Caraco et al. 1991). Sulfate is abundant in sea salt. A similar feedback among algal production, anoxic events, and P recycling has been modeled for marine systems (Van Capellen and Ingall 1994; Tyrrell 1999).

In shallow lakes or seas, P can be recycled by physical mixing of sediments by waves or bottom-feeding fishes (Scheffer et al. 1993; Jeppesen et al. 1998; Scheffer 1998). Feedbacks among water clarity, macrophytes, and bottom-feeding fishes result in two quasi-stable states—one with macrophytes, clear water, and few bottom-feeding fishes and the other with turbid water, no macrophytes, and abundant bottom-feeders. Models of shallow lakes are well understood (Scheffer 1998; Scheffer et al. 2001a, 2001b). The extent to which these models can predict lake dynamics is currently an area of active research.

Fish predation can change grazer communities and thereby change chlorophyll concentrations or primary production of pelagic systems (Carpenter and Kitchell 1993). The grazer community affects phytoplankton through direct consumption as well as excretion of P. Examples of food web impacts on phytoplankton are known from both lakes and oceans (Carpenter 2003). In lakes, the impact of grazers on chlorophyll or primary production can often be predicted from measurements of the body length of crustacean zooplankton (Pace 1984; Carpenter and Kitchell 1993). A simple empirical model of grazer effects substantially reduced the variance of predicted chlorophyll when the model was applied to a cross-section of North American lakes (Carpenter 2002).

Mechanistically rich simulation models have been used to understand or manage eutrophication in many situations (Chapra 1997; Xu et al. 2002). Such models address a diversity of climatic, biogeochemical, and biological factors that may affect eutrophication. Although these models have a number of fundamental similarities, such as the central role of nutrient supply, they also include a number of site-specific features (e.g., Bartell et al. 1999; Drago et al. 2001; Everbecq et al. 2001; Gin et al. 2001; Håkanson and Boulion 2003; Karim et al. 2002; Pei and Wang 2003). Because of the diversity and site-specificity of this family of models, it was not possible to recommend one particular mechanistic model for use by the MA.

Recycling and food web dynamics create threshold behaviors in the P cycle (Carpenter 2003). For the MA, the most important thresholds are those that, if crossed, create self-perpetuating eutrophication of a water body. These thresholds are difficult to discern before they are crossed (Carpenter 2003). For example, in a region of Wisconsin in the United States with generally high water quality, nearly half of the lakes were judged susceptible to self-perpetuating eutrophication (Beisner et al. 2003). Extensive regional data bases and whole-lake experiments that deliberately eutrophied three experimental lakes were necessary to make this calculation. Comparable data are available for few other regions of the world.

At present, validated and generally applicable models for the prediction of eutrophication thresholds do not exist. Certain key elements of such models are present in the research summarized here, but these elements have not been aggregated in a globally applicable modeling framework. Statistical studies of eutrophication thresholds reveal broad confidence intervals, indicating that uncertainties about the location of thresholds are high (Carpenter 2003).

4.6.1.2.3 Models for interaction of policy and water quality

Some policy-related models have addressed water quality, eutrophication, or harmful algal blooms. For example, the global scenario model PoleStar (Raskin et al. 1999) presents water quality indicators. The water quality module of PoleStar is relatively simple (and therefore readily testable with data where these exist) and transparent and has been used in a number of global scenario exercises.

For single lakes, stochastic dynamic optimization models have been used to determine optimal P input in the presence of thresholds and uncertainty about parameters (Carpenter et al. 1999b; Ludwig et al. 2003). Variants of these models have been used to study the possibility of estimating the thresholds for eutrophication by active adaptive management (Carpenter 2003; Peterson et al. 2003). The general finding is that someone is unlikely to learn the threshold without crossing it and thereby eutrophying the lake (Carpenter 2003).

Various other models have been used to study economic, social, or political processes that interact with ecosystem dynamics to determine ecosystem services derived from fresh water (Brock and de Zeeuw 2002; Guneralp and Barlas 2003; Janssen 2001; Scheffer et al. 2003; Tundisi and Matsumura-Tundisi 2003). These include comparisons of policies that maximize a measure of expected net utility over long time horizons as well as game theory models of stakeholder interactions. Other models have considered the dynamics of uncertainty about thresholds as managers attempt to maximize expected net utility for lake ecosystem services (Carpenter et al. 1999a; Janssen and Carpenter 1999; Carpenter 2003; Peterson et al. 2003). Extensions of such models in the form of computer games can be used to help stakeholders understand the vulnerabilities of water quality and form expectations that are consistent with sustainable use of fresh waters (Carpenter et al. 1999b; Peterson et al. 2003).

4.6.2 Critical Evaluation of Approaches

4.6.2.1 Phosphorus Transport Models

Phosphorus transport models can provide reasonably accurate estimates of P transport, especially in small, agricultural watersheds, for which most of them were developed. A recent review by Sharpley et al. (2002) provides an excellent overview of data and relationships available to update P transport models.

Applications of transport models are often limited by lack of data available for the detailed parameterization that is necessary. The more realistic these models attempt to be in terms of mechanisms of P transport, the more data they require. Predicting P transport may require highly accurate land use maps, digital elevation models, and data about fertilizer and manure use, including the P content of the manure. Increasing mechanistic detail, watershed size, or spatial resolution can quickly cause run times to become extremely long and the models themselves to be difficult to apply (Sharpley et al. 2002).

In addition, many models of P transport are designed to simulate P transport only in small-scale agricultural systems (Gburek and Sharpley 1998). The accuracy of scaling-up is dependent on how processes at finer scales relate to processes that govern P transport at larger, watershed scales (Sharpley et al. 2002). These models were unlikely to be useful for quantifying distinctions in the MA scenarios at global scales due to difficulties in generalizing across differences in the processes that drive eutrophication around the world.

Most P transport models are not linked to models that simulate impact of P on the aquatic ecology (Wade et al. 2002). Linking these two models in order to understand the impact of land use and management strategies on aquatic ecosystems will be an important next step for researchers and watershed managers.

4.6.2.2 Freshwater Eutrophication Models

Empirical eutrophication models of the type introduced by Vollenweider (1968) could provide a robust foundation for eutrophication estimates. Advantages of the empirical models include a long history of usage leading to considerable information about strength and limitations of the models, simple transparent mathematical structure, and the possibility of rigorous uncertainty analyses. Limitations of empirical models include uncertainty of extrapolation beyond the conditions of the data used to fit the regressions and the rather wide confidence intervals of prediction. Cole et al. (1991) and Pace (2001) discuss the strengths and limitations of empirical models in ecosystem science.

The simple empirical models omit a number of important effects. For the quantification of the global scenarios of MA, however, it was impractical to obtain data on these other factors at the necessary scales.

Recycling and food web effects are two important omissions from the simple P input models to predict chlorophyll. For the purposes of MA, these omissions probably caused simple empirical models to underestimate chlorophyll and the harmful effects of eutrophication under conditions when P recycling was likely to be high. These include situations in which there has been a long history of high P input, causing sediments to become enriched with P; water temperatures were warm (Nürnberg 1995); or ecosystems have received high inputs of sulfate (such as emissions from burning coal). Overfishing of top trophic levels may cause cascading effects that exacerbate eutrophication. In summary, then, the simple P input models could underestimate the severity of eutrophication in warmer regions of the world or under conditions of chronic heavy loading, climate warming, or food web transformation by fishing. These are the future conditions that needed to be addressed in some MA scenarios.

In situations where extensive data on lake morphometry, biogeochemistry, hydrodynamics, and food web structure are available, it may be advisable to use more detailed models to predict eutrophication. Pragmatically speaking, however, the current global data bases are not likely to provide enough detail to warrant one of these more sophisticated modeling approaches.

4.6.3 Research Needs

Many of the P transport models presented here require a large amount of data to be parameterized and calibrated for the particular watershed or region in question. Yet the underlying principles are similar, and it should be possible to develop more generally applicable P loading models. Improved spatial data sets for soils and topography (digital elevation maps) will also advance our ability to predict P loads. Better information is needed about how soil P concentrations and pools interact with land use and change in land use to affect P transport. Because P transport is affected by soil type, vegetation type, climate, and many other local variables, it has been difficult for researchers to generalize about P transport while attempting to model transport in a specific watershed. Sharpley et al. (2002) present an overview of the generalizations for which data exist.

While eutrophication may appear to be a regional problem, it is related to global changes that people are making to the P cycle through mining and widespread use of fertilizers (Bennett et al. 2001). Eutrophication of a given lake is not independent of eutrophication happening elsewhere; it is a global pattern. Developing simple large-scale or even global models that can be used to indicate P use, transport, and eutrophication based on land use should be a priority.

Developing models to understand the impact of land use change on P transport is also important. At present, the available models assume that the process of land use change does not release P (Wickham et al. 2000, 2002). That is, they figure that if agriculture exports equal X g P/ha and urban exports equal Y g P/ha, converting agricultural area to urban decreases P export by X-Y g P/ha. However, several studies have indicated that the period of transition to urbanized use is a critical period of high P transport (Kaufman 2000; Owens et al. 2000). Models that address the impact of this period of transition are important. Development of these models will require land use change data as well as a better quantitative data about the impact of periods of land use transition on P transport.

A priority for freshwater eutrophication models is developing a better understanding and predictive capability for internal recycling and sequestration mechanisms (including those mediated by organisms, especially invasive species). The interaction of internal recycling and sequestration with loading processes will be a critical aspect of this understanding. Although some models have been developed for integrating management with transport and eutrophication models, further development of models that integrate human interventions (including management actions) to water quality, aquatic ecosystem services, and human well-being is needed.

4.7 Forecasting Changes in the Nitrogen Cycle and Their Consequences

The nitrogen (N) cycle is a key regulator of the Earth system, linking terrestrial, marine, photochemical, and industrial processes. Biodiversity, carbon storage, and atmospheric chemistry are all regulated in part by the cycling of reactive nitrogen compounds. Over the last century and a half, expansion and intensification of agriculture together with fossil fuel combustion have led to an acceleration of natural microbial N cycling and have more than doubled N inputs to terrestrial ecosystems. Measurable results of these perturbations include a 17% increase in the atmospheric concentration of nitrous oxide (N_2O), a potent greenhouse gas, and a doubling of dissolved nitrogen export from rivers to coastal zones and of natural reactive nitrogen emissions to the atmosphere (Galloway et al. 2004). Since many of the effects of human N cycle perturbations are difficult to measure directly, ecosystem models play an important role in assessing and quantifying past and present impacts and in making future predictions.

4.7.1 Existing Approaches

4.7.1.1 Transport Models

4.7.1.1.1 Process-based models of the terrestrial nitrogen cycle

A number of models have been developed to simulate nitrogen biogeochemistry. The simulation of net primary productivity is central to all of these models. NPP is either derived from satellite normalized difference vegetation index data (Potter et al. 1996; Asner et al. 2001) or calculated as a function of climatological inputs like temperature, solar insolation, and precipitation (which drives the soil water balance component of the models). In terrestrial models that simulate the coupled carbon-nitrogen cycle, including CENTURY, TEM, BIOME-BGC, pNET, and the NCAR CLM2, the calculation of NPP is modulated by nutrient limitation—that is, soil nitrogen availability (McGuire et al. 1992; Aber et al. 1997; White et al. 2000; Parton et al. 2001; Bonan et al. 2002).

The availability of mineral nitrogen in the soil is controlled at short time scales by soil temperature and moisture conditions, at intermediate time scales by the supply of new organic matter from plant litter and decomposition of existing organic matter, and at longer time scales by changes in litter quality due to changing plant community composition and soil texture. In the absence of anthropogenic inputs, on very long time scales (decades to centuries), the composition of natural plant communities depends on the balance between accumulation and loss of fixed nitrogen, with accumulation from N deposition and from the symbiotic and asymbiotic fixation of atmospheric N_2 and with loss due to leaching and transport in outflow, microbial dentrification, and denitrification during biomass burning.

The different processes that determine soil N availability are simulated by current models with varying degrees of sophistication. Many terrestrial models have multiple compartments describing woody and herbaceous litter and rapidly and slowly degrading soil organic matter pools (Parton et al. 1987). These models contain detailed algorithms for soil organic matter dynamics that include competition between plants and soil biota for soil mineral nitrogen resources and nitrogen constraints for carbon assimilation and allocation to different plant tissues. Some models, like the NCAR CLM2, are beginning to incorporate dynamic vegetation algorithms, with explicit competition between multiple plant functional types for common soil water and mineral nitrogen resources, which allows for evolution of plant communities in the face of human perturbations and global change (Bonan et al. 2002).

In contrast to these relatively sophisticated algorithms, other key processes like N_2 fixation are still parameterized rather crudely—for example, as simple functions of precipitation or based on biome type (Parton et al. 1987). Furthermore, a recent assessment of terrestrial N_2 fixation, based on a compilation of measurements from different ecosystems, revealed a large uncertainty (a range of 100–300 Tg N/yr) in the global terrestrial fixation rate (Cleveland et al. 1999).

4.7.1.1.2 Modeling N export in rivers

A major consequence of N cycle perturbation is the increased transport of leached N in rivers to coastal regions. Increased N loading in coastal areas can stimulate harmful algal blooms and associated heavy loads of decaying organic matter, which can lead to hypoxic or anoxic conditions. This phenomenon, known as eutrophication, is often accompanied by changes in plant and algal species composition, fish death, coral reef degradation, and decreases in species diversity (NRC 2000). In extreme cases, such as the outlet of the Mississippi River into the Gulf of Mexico, eutrophication can turn coastal waters into "dead zones" (Rabalais et al. 2002). Increased N delivery to coastal areas also can lead to enhanced microbial production of nitrogen trace gases, including NH_3 and the greenhouse gas N_2O (Naqvi et al. 2000).

In recent years, a number of studies have attempted to quantify and identify the origin of N exported in rivers to coastal regions. These studies generally have used empirical models to relate N export in rivers to various independent variables, including basin runoff , land cover type, soil texture, human population, and N inputs from fertilizer, sewage, and atmospheric deposition (Seitzinger and Kroeze 1998; Caraco and Cole 1999; Lewis et al. 1999; Alexander et al. 2000; Lewis 2002; R. A. Smith et al. 2003; S. V. Smith et al. 2003). The statistical models range from simple linear regressions to complex nonlinear matrix inversions.

Recently, Donner et al. (2002) published the first process-based simulation of N transport in rivers on a regional scale. Their study coupled water runoff rates from a carbon-only terrestrial ecosystem model to prescribed N leaching fluxes and a hydrological routing model for the Mississippi River basin. The study did not account for increases in fertilizer and other anthropogenic N inputs over time, since its main purpose was to isolate the effect of changes in hydrology (that is, increased runoff) on N export in the Mississippi River from 1955 to 1996.

Although the terrestrial ecosystem model used in Donner et al. (2002) was a carbon-only model, most of the terrestrial coupled carbon-nitrogen biogeochemistry models just discussed explicitly calculate NO_3-leaching rates as well as water runoff rates. These models commonly calculate an N leaching term at each individual grid cell, which goes into a global accounting pool but otherwise effectively leaves the grid cell and disappears from the model. Future improvements in N cycle modeling will involve coupling terrestrial N leaching rates to hydrological and river routing models, permitting evaluation of downstream and long-term impacts of N leaching.

4.7.1.1.3 Ocean and coastal nitrogen biogeochemistry models

Human N cycle perturbations have impacts not only on terrestrial ecosystems but also on coastal regions and, potentially, on the open ocean. The transport of leached N in rivers to coastal regions and its stimulation of coastal eutrophication have already been described. In addition, a significant fraction of the reactive NH_3 and NO_x volatilized from soil and produced by fossil fuel combustion eventually deposits on coastal or open ocean waters (Holland et al. 1997; Paerl 2002). Global change may also have profound impacts on oceanic N cycling through other physical and chemical mechanisms, such as decreases in ocean pH associated with increasing atmospheric CO_2 and enhancement of thermal stratification due to global warming. The latter may increase water-column O_2 depletion, thus promoting denitrification (Altabet et al. 1995).

Three-dimensional ocean biogeochemistry-circulation models have historically not been well designed to simulate the impact of anthropogenic N inputs on the oceanic nitrogen cycle. Most early ocean carbon models were constructed around phosphorus as the limiting nutrient, in large part to avoid the complications of simulating biological sources and sinks of oceanic fixed N. Furthermore, rather than being computed mechanistically, oceanic primary production and associated organic matter remineralization were estimated as the fluxes needed to produce dissolved phosphate concentrations that match observed climatologies (Najjar and Orr 1998).

An additional complication is that Fe rather than N appears to be the limiting nutrient in high nitrate–low chlorophyll regions of the sub-tropical North Pacific and the Southern Ocean, where enhancements in primary production could lead to significant increases in oceanic sequestration of fossil CO_2. As a result, most recent model and empirical studies of oceanic nutrient limitation have focused on Fe (Fuhrman and Capone 1991; Moore et al. 2002b; Jin et al. 2002). Some of these studies have predicted that Fe fertilization may stimulate oceanic primary production and accompanying remineralization and nitrification, with a resulting increase in oceanic N_2O production. The resulting increase in atmospheric N_2O could offset or even outweigh the gains in greenhouse gas reduction associated with CO_2 sequestration. However, a better understanding of oceanic N_2O production and an improvement in its parameterization in ocean models are needed before such simulations can be fully credible.

As in terrestrial ecosystems, the importance of oceanic biological N_2 fixation is not well understood. Current estimates of oceanic N_2 fixation range over an order of magnitude (Gruber and Sarmiento 1997; Codispoti et al. 2001). The rate of oceanic denitrification is also uncertain, although current global estimates are somewhat better constrained, thanks to geochemical tracer studies (analyses based on observed nitrate:phosphate ratios) (Howell et al. 1997; Deutsch et al. 2001). The balance between oceanic N_2 fixation and denitrification, together with riverine N inputs, ultimately determines the availability of oceanic fixed N to primary producers and has been hypothesized in simple box model studies to regulate atmospheric CO_2 levels on millennial time scales (Falkowski 1997). Progress is being made in reconciling estimates of ocean N_2 fixation and denitrification derived from biological extrapolations versus geochemical tracers, thereby providing improved constraints on these important N cycle fluxes (Hansell et al. 2004).

Other promising developments in coastal and oceanic N cycle modeling include the development of regional approaches to estuarine and coastal nutrient biogeochemistry, which involve embedding higher resolution regional submodules and/or off-line regional and global compartment simulations and databases (Jickells 2002; Mackenzie et al. 1998). In addition, open ocean ecosystem models that move away from climatological ''nutrient-restoring'' approaches and toward more process-based simulations are under development. Such models include multinutrient (NO_3, NH_4, PO_4, SiO_3, Fe) limitation and explicitly resolve community structure (picoplankton, diatoms, calcifiers, diazotrophs) in the upper ocean (Moore et al. 2002a, 2002b; Le Fevre et al. 2003).

4.7.1.2 Models Emphasizing Feedback between Nitrogen and Key Ecosystem Processes

4.7.1.2.1 Modeling N regulation of NPP

Models such as the Terrestrial Ecosystem Model and Biome BGC have examined the influence of vegetation C:N ratio, and its consequent feedbacks on soil N availability, in regulating NPP. These models have demonstrated why temperate forest ecosystems, which have large, carbon-rich woody vegetation fractions and wide C:N leaf ratios, tend to be chronically N-limited (McGuire et al. 1992; White et al. 2000). In contrast, humid and dry tropical forests, which contain N-rich vegetation, are more likely to be limited by phosphorus (Vitousek 1994). The TEM model has also demonstrated the importance of considering N availability in predicting how climate change will affect NPP (Rastetter et al. 1992). Models that consider carbon biogeochemistry alone tend to predict an increase in soil respiration at warmer temperatures and therefore net CO_2 loss to the atmosphere from soil organic carbon. However, models that consider coupled carbon-nitrogen dynamics predict an increase in soil N mineralization rates and therefore soil N availability that can help increase NPP and thus offset soil carbon losses.

4.7.1.2.2 Modeling N trace gas emissions from terrestrial ecosystems

The ''leaky pipe'' model of Firestone and Davidson (1989) provides the conceptual framework for estimating microbial NO_x, N_2O, and N_2 emissions from soils. Soil gas diffusivity, a function of soil type and soil water content, regulates the partitioning of N trace gas in this conceptual model. Low soil gas diffusivity favors the emission of N_2 over N_2O and N_2O over NO_x.

The leaky pipe model has been incorporated into some process-based model algorithms. For example, the CASA model estimates N trace gas emissions as a fixed fraction (say, 1–2%) of the rate of soil N mineralization, with a soil-moisture dependent partitioning between NO_x and N_2O (Potter et al. 1996). The N gas sub-model of CENTURY uses calculated soil water content, temperature, and microbial N cycling rates to simulate daily N_2, N_2O, and NO_x emissions from nitrification and denitrification. A daily time step is used because this degree of resolution is needed to reproduce the short-term events that are often responsible for the majority of N gas emissions from soils (Parton et al. 2001). The daily time step is also more appropriate to the needed coupling to atmospheric chemistry transport models.

NH_3 emissions are largely associated with volatilization from livestock manure and ammonium fertilizers and are equal to or exceed NO_x emissions on a global scale. Modeling of NH_3 emissions is generally based on simple empirical regression models (which are also used to estimate NO_x and N_2O losses from fertilizer) (Bouwman et al. 2002). Alternatively, some process-based models like CENTURY estimate immediate NH_3 volatilization losses as a product of the livestock manure or fertilizer input and a soil texture-dependent emission coefficient.

Soil N trace gas models have been successfully evaluated at specific test sites (Parton et al. 2001), although the extrapolation of model results to the regional and global scales is still highly uncertain. An additional shortcoming of current trace gas emission models is that they do not track the atmospheric transport, chemical transformation, and deposition of NH_3 and NO_x, and they thus neglect additional emissions and other effects that may occur downwind.

4.7.1.2.3 Feedbacks between N fluxes and ecosystem response

Much of the anthropogenic NO_x and NH_x emitted to the atmosphere as a result of agriculture, fossil fuel combustion, and other human activities deposits close to its point origin. However, a portion may be transported long distances, crossing national boundaries and even oceans before depositing. The lifetime of NO_x and NH_x in the atmosphere is short (hours to days), but these reactive species can be transformed to longer-lived species such as HNO_3 and PAN or may simply escape the boundary layer and be rapidly transported in strong upper tropospheric winds.

Long-distance transport of NH_x and NO_y can have profound impacts on downwind ecosystems. N deposition on formerly pristine natural ecosystem, such as N-limited grasslands, forests, and aquatic systems, in some cases can stimulate productivity, leading to increased carbon uptake and storage (Galloway et al. 1995; Holland et al. 1997). In other cases, excessive N deposition can cause acidification, forest decline, a decrease in plant species diversity, declining production, and C storage and accelerated N losses (Galloway et al. 1995; Vitousek et al. 1997; Aber et al. 1998). N deposition onto formerly pristine areas can also alter the emission and uptake of other trace species. For example, N deposition can lead to increased N_2O emissions (Mosier et al. 1998) and decreased soil consumption of atmospheric CH_4, which is also important greenhouse gas. Both increased N_2O emissions and decreased CH_4 consumption contribute to increased radiative heating of Earth's atmosphere.

Northern temperate forest ecosystems, which are often located downwind from centers of fossil fuel combustion, have seen the greatest changes in N inputs from the atmosphere and have been the focus of most terrestrial biogeochemical modeling studies. Models have predicted an initial stimulation of NPP in these generally N-limited ecosystems, followed in some cases by eventual N saturation, which is characterized by increased nitrate leaching rates and ultimately declining forest productivity (Aber et al. 1997). The TerraFlux model has been applied to biomes other than temperate forests, notably semiarid and tropical regions, where much of the future growth in atmospheric N deposition is projected to occur. These ecosystems may respond to excess N in markedly different ways than temperate forests and may be more likely to suffer deleterious effects. TerraFlux results suggest that N-rich tropical forests may have reduced productivity following excess N deposition, associated with increased leaching of NO_3 and the related loss of important, potentially nutrient-limiting cations like Ca+2, Mg+2 (Asner et al. 2001). However, TerraFlux predicts increases in productivity in semiarid systems following N input if water availability is sufficient and water losses are moderate.

4.7.2 Critical Evaluation of Approaches

One of the major weaknesses in current N cycle models is that they fail to account for the significant fraction of anthropogenic N inputs to terrestrial ecosystems that is denitrified (lost to gaseous N_2 or N_2O), reassimilated into biomass, or stored within groundwater or wetlands before reaching rivers. Detailed N budget studies in individual watersheds have found that only approximately 15–25% of N fertilizer and other inputs to watersheds ends up in rivers (Howarth et al. 1996; Caraco and Cole 1999). Typically, ~40% of N inputs to watersheds cannot be accounted for (Howarth et al. 1996). This missing N is assumed to be denitrified or stored in the landscape. A relatively smaller fraction of N inputs (~10%) is observed to be denitrified within rivers. Improved accounting for N losses that occur in between the soil leaching and coastal delivery stages is necessary for a credible simulation of the impact of human N cycle perturbations in a comprehensive Earth System model.

4.7.3 Research Needs

Addressing the changing nitrogen cycle and ecosystem services requires a variety of models at a range of temporal and spatial scales, from local to global. One of the clear gaps in our knowledge is in modeling the dynamics of coupled systems, in which terrestrial and atmospheric systems interact with economic trends or cycles. Coupled models, including coupling among the biogeochemical cycles, will need to be improved so that they can anticipate the crossings of thresholds that yield entirely new ecosystem states. More specifically, we must move toward an integrated model of the terrestrial, aquatic, and atmospheric components of the nitrogen cycle, which encompasses the complex feedback-response relationships and key nonlinearities of the cycle. Such a whole Earth system model should include terrestrial biogeochemistry models coupled with atmospheric chemistry/dynamics models, river transport models, and coastal and open ocean biogeochemistry/circulation models.

4.8 Forecasting Fish Populations and Harvest

The goal of fisheries assessment is to predict the consequences of fishing and other environmental interventions and, on that basis, evaluate how different management schemes fare at achieving various management goals. Forecasting the state and harvest of exploited populations and communities is thus central to fishery science.

There are two broad approaches that can be used to forecast fisheries population and harvest. On the one hand, there are short-term forecasts aimed at predicting the size of the exploitable stock for the upcoming fishing season in order to implement a predetermined feedback harvest rule. In this case, the forecast is part of the tactic used to define regulatory measures for the fishing season, such as the total allowable catch or the number of allowable effort units. This type of forecast is critical for fisheries based on short-lived or semelparous species (species that reproduce once and then die), where the bulk or all of the annual catch is made up of new recruits.

Mid- and long-term forecasts of populations, on the other hand, are used in policy design to examine likely consequences of different management options and thus guide strategic decision-making. In contrast to short-term tactical forecasts, mid- and long-term forecasts are not meant to actually predict the future of the system under exploitation; rather, they attempt to represent a full range of scenarios that are deemed possible based on historical experience. Because our ability to actually predict the responses of natural systems to harvest is admittedly limited, the emphasis in policy design is on feedback and robustness of performance across scenarios. Mid- and long-term forecasts aimed at guiding general management approaches are difficult because they require more information than the most recent harvest rates and data on catch per unit of effort, but it is not clear which of many possible auxiliary data will be most useful or how much history to consider.

4.8.1 Existing Approaches

The basic approach to fisheries forecasting has three components: a mathematical model used to describe the dynamics of the system under study as it is impacted by fishing, an approach used to condition the model on available information, and numerical tools used to implement forecasts under various management regimes.

4.8.1.1 Single-Species Approaches

Fisheries assessment and management have been dominated by single-species approaches aimed at controlling fishing impacts on unitary stocks by considering them in isolation from the ecosystem of which they are part. As a result, quantitative methods used for fisheries forecasting and policy evaluation have emphasized single-species modeling.

4.8.1.1.1 Models

Models used to represent single-stock dynamics range widely in complexity. The simplest models correspond to biomass-aggregated stock-production models, such as the Schaefer or Pella Tomlinson models (Quinn and Deriso 1999), which specify production as a simple nonlinear function of aggregate stock biomass. Surplus production is zero when the stock is at carrying capacity, and it increases to some maximum at some intermediate stock size. An increase in realism relative to simple stock-production models is achieved in the so-called delay-difference models (Deriso 1980; Quinn and Deriso 1999) by explicitly modeling the separate contributions of growth and births (actually recruitment of new-year classes to the exploited stock) to stock production. In these models, the stock is represented by the aggregate biomass of the exploited, mature component, animals recruit to the stock at some age r, and annual recruitment is a stochastic function of the mature biomass r years earlier. Generalized versions of this model include equations to predict the changes in size composition of the exploited stock (Hilborn and Walters 1992).

The models most widely used for fisheries forecasting are substantially more complex, including a representation of the age and size structure of the stock as well as age/size-specific fishing mortalities. As in delay-difference models, stochastic, density-dependent stock-recruitment relationships of various types are used to generate recruitment as a function of mature biomass. The standard Virtual Population Analysis and statistical catch-at-age models (Hilborn and Walters 1992; Quinn and Deriso 1999) used commonly for fish stock assessment and forecasting belong in this class. Finally, even more complex are models that incorporate spatial structure in addition to age or size structure, such as MULTIFAN CL (Fournier et al. 1998; Hampton and Fournier 2001). Each increase in realism is achieved by an increase in the number of parameters. For example, while a single fishing mortality rate per year is used in stock-production and delay-difference models, a vector of age/size-specific mortality parameters per year is used in standard age/size-structured models.

Forward projections constructed with these models always include stochasticity in at least some of the key processes. Recruitment variability induced by environmental forces is usually the dominant source. Typically, this variability is captured using a probabilistic distribution (such as log-normal with independent or autocorrelated random-year effects) as an empirical descriptor without attempting to model the actual environmental factors and processes underlying the variability. The inclusion of regime shifts in some of the scenarios (e.g., MacCall 2002; Parma 2002a, 2002b) is becoming more common, as empirical evidence is gained in their support (Francis and Hare 1994, 1998).

4.8.1.1.2 Conditioning approaches

Whichever the structure of the population model, its parameters are estimated by fitting time series of data on the stock and its fishery or fisheries, often making use of other sources of relevant information, such as information "borrowed" from other similar stocks. Fishery models are conditioned using formal statistical methods based on maximum likelihood or, increasingly, Bayesian techniques (Hilborn and Mangel 1997; Punt and Hilborn 1997, 2002). Maximum likelihood methods aim at providing best point estimates of abundance and fishing mortality rates over time and their associated estimation error. By contrast, Bayesian methods are used to derive joint probability posterior distributions of model parameters (and functions of them), conditioned on all observations and prior information.

Models are fitted to different types of data, depending on model complexity. Most critical for the estimation of the level of stock depletion is the availability of indices of stock abundance. These are derived from research surveys or commercial catch per unit of effort. Tagging data can also be used to provide information on abundance or exploitation rates. In addition, age/size-structured models use information on the age/size composition of the commercial and survey catches to help estimate trends in year-class strength. All these different sources of information are generally analyzed using an integrated statistical approach, where the likelihood function has several components, one for each type of data, with each based on a probability model deemed appropriate for the data in question. When estimation is done using Bayesian methods, prior information other than hard data may also be incorporated (e.g., McAllister et al. 2001).

Advances in computer technology and development of efficient methods of nonlinear estimation (such as use of automatic differentiation in AD Model Builder; available at www.otter-rsch.com/admodel.htm) have made it possible to build very complex models that incorporate process variability in many parameters assumed to be constant in simpler models. For example, fishing catchability and selectivity may be assumed to vary over time according to some specified random process. While in the past, estimation was done assuming that either all the noise was due to measurement error or process error, the new generation of fishery models incorporate both process and measurement error in the estimation.

4.8.1.1.3 Numerical tools

Monte Carlo techniques are used to simulate future stock trajectories incorporating different sources of uncertainty, as discussed below. Bayesian Markov Chain Monte Carlo methods (Punt and Hilborn 1997, 2002) are increasingly used to approximate posterior distributions of model parameters and then sample from them to project populations under various candidate fishing policies (e.g., Patterson 1999; Parma 2002a, 2002b).

4.8.1.2 Multispecies Approaches

Concerns about the impacts of fisheries on non-target species, habitats, and marine communities have increased over the last decade, leading to strong pressure to move from single-species management to ecosystem management. This has encouraged further developments of ecosystem models, which are needed to address the type of questions now being posed to fisheries assessment scientists.

4.8.1.2.1 Generalizations of single-species models to include features of multispecies systems

The simplest way in which multispecies effects have been incorporated into single-species fishery models is by adding mortality terms to represent the effects of predation on a target species. The dynamics of the predator is not explicitly modeled but instead is used as a driving variable in modeling the dynamics of the target species. Walters et al. (1986), for example, modeled the stock-recruitment relationship of Pacific herring (*Clupea harengus*) as affected by the abundance of its main predator, Pacific cod (*Gadus macrocephalus*). Similar models have been developed for pollock (*Theragra calcograma*) in the eastern Bering Sea (Livingston and Methot 1998) to assess the influence of predation and climate effects on recruitment. Also, Punt and Butterworth (1995) used a three-species model to evaluate the impact of culling the predator fur seals (*Arctocephalus pusillus pusillus*) on the abundance and catches of the Cape hakes *Merluccius capensis* and *M. paradoxus*. They considered this to be the "minimal realistic model" needed to examine their question and emphasized that great care needs to be taken when designing such models to ensure that all the important predator-prey interactions are incorporated.

A coarse approach for applying single-species models to multispecies systems are the so-called aggregated production models (Hilborn and Walters 1992), which simply apply stock-production models (biomass logistic models with harvest) to aggregates of species. These models have been tuned to time series of catch rate and fishing effort. Ralston and Polovina (1982) found that in several tropical fisheries, trends in catch rate and yield for mixed-species assemblages were consistent, while results from production models applied to single-species were erratic.

4.8.1.2.2 Multispecies "top-down" models based on the mass action principle

Most of the early multispecies fishery models rely on the mass action principle to represent predator-prey interactions (Walters and Martell in review). Under this principle, the number of encounters between species is proportional to the product of their densities. Predation rates, whether or not they are affected by predator satiation and handling time (so-called type II functional response by predators), are directly predicted from such encounter rates. These models generally predict very strong "top-down" control of abundances by predators.

The simplest models based on the mass-action principle are generalizations of single-species stock-production models. They depict the biomass dynamics of multiple species using logistic models linked by Lotka-Volterra predator-prey equations (Larkin and Gazey 1982).

A second approach is multispecies virtual population analysis (Sparre 1991), a detailed age-structured model with age-specific harvest and predation rates, originated in the North Sea model of Andersen and Ursin (1977). MSVPA focuses on the interactions between commercially exploited fish stocks for which catch-at-age data are available. It assumes that individual food intake and growth are constant, and it uses data on stomach contents of all modeled species to estimate prey suitabilities. Historical trends in abundance are estimated from historical catches. A forecasting version of MSVPA, MSFOR, is being applied to the analysis of exploited ecosystems of the North Sea (Rice et al. 1991; Vinther et al. 2002) and eastern Bering Sea (Jurado-Molina and Livingston 2002).

4.8.1.2.3 Mass balance multispecies approaches

While all the previous approaches are conditioned on past data on the dynamic states of the populations represented, mass-balance methods are founded on a static description of the ecosystem, represented by biomasses aggregated into ecologically functional groups. The basic idea behind the mass-balance assumption is that for the collection of functional groups considered, production ought to be balanced by predation, harvest, migration, and biomass change. The most widely used mass-balance model is Ecopath, which is based on static flow models (Polovina 1984; Christensen and Pauly 1992), defined by a series of simultaneous linear equations that represent trophic interactions and fishing. The essential parameters required for each functional group are generally the same as those of other multispecies models—namely biomass, production rate, consumption rate, diet composition, and fisheries catch. One extra parameter per group controls the fraction of the production that is accounted for in the model. The diet composition matrix plus four of the five group-specific parameters need to be "known," and the mass-balance equations are solved for the remaining parameters.

Unlike MSVPA, Ecopath uses data on the production/biomass ratio as input (Christensen and Walters 2000). Ecopath does not require a representation of individual species or their age structure. Another difference between the two approaches is that while MSVPA considers the subset of commercially important species and their key preys and predators, Ecopath attempts to portray ecosystem-wide dynamics, including primary production.

Ecosim is a dynamic extension of Ecopath that simulates time trajectories of the different functional groups modeled and thus can be used to examine influences on ecosystem dynamics resulting from any given harvest policy (Walters et al. 1997). Ecosim replaces the static biomass flow of Ecopath by a system of differential equations but it retains the mass-balance assumption of Ecopath by tuning the model to the baseline observations on biomasses and consumption rates of the functional groups at a given reference time. We should note that this does not imply equilibrium; known changes in biomasses can be incorporated in the Ecopath biomass flow equations.

A fundamental difference with mass-action models is the introduction in Ecosim of the foraging arena concept (Walters and Juanes 1993; Walters and Martell in review), by which only a dynamic fraction of each ecosystem component is vulnerable to predators. The fact that parts of the prey populations are not vulnerable effectively augments bottom-up effects compared with typical Lotka-Volterra-based models. Through alternative parameterizations, users can represent a variety of assumptions about the nature of predator-prey interactions.

Ecopath with Ecosim software is a widely used tool for the quantitative analysis of food webs and ecosystem dynamics (e.g., Pauly et al. 2000), and new capabilities are being constantly developed. In particular, the software can input historical trends in fishing mortality or effort, productivity indices (such as upwelling), recruitment indices, and biomass of other, nonmodeled species to drive the dynamics. Also, predicted trends can be fitted to observed trends in relative or absolute abundances, to direct estimates of total mortality rate, and to historical catches. Advanced users are beginning to experiment with fitting the model to time series data using formal statistical methods, but this is in its early stages of development compared with single-species approaches.

4.8.2 Critical Evaluation of Approaches

4.8.2.1 Uncertainty Analysis

Our limited ability to forecast population abundances and catches has several roots: observation uncertainty, process uncertainty, model uncertainty, and institutional uncertainty.

First, we do not "observe" marine populations directly, nor do we observe all the relevant variables to be able to estimate population abundance confidently and understand the relationships that govern their interactions. Errors in estimates of current exploited stock sizes obtained by modern assessment methods commonly exceed 30% (NRC 1998). Much larger errors, as large as 200%, have resulted from the use of flawed assessment models (Walters and Maguire 1996). The abundance of other unexploited ecosystem components may be even less known. This means that there is substantial uncertainty about the initial conditions of the variables involved in running any forecast model. Imprecision and biases in diet composition data used to parameterize predator-prey relationships are also a problem. In particular, Walters and Martell (in review) have cautioned about the risk of missing small prey items infrequently eaten by abundant predators, a phenomenon that may strongly affect prey dynamics.

Second, natural processes are inherently variable, and no matter how good our models may be, they cannot predict the exact state of the system at any given time in the future. In marine populations, most life histories involve an early larval stage that is subject to the vagaries of the planktonic environment. As a result, variability in recruitment contributes substantial process uncertainty (Botsford and Parma in press). Oceanic processes are subject to large-scale decadal oscillations, as well as episodic events like El Niño that alter primary production and hence fish productivity. It has proved very hard to build these environmental drivers into fishery models.

Third, models consist of relationships between variables (functional or probabilistic) and parameters, and there is uncertainty in both: structural uncertainty and parameter uncertainty. As a rule, many alternative models are consistent with experience and historical data, but some model uncertainties are more critical than others. For example, the productivity of a stock at low biomass is critical for the estimation of sustainable harvest rates; uncertainty about the stock structure and the proper spatial resolution to consider may affect interpretation of most observed patterns; different parameterizations of predator-prey relationships may completely change the behavior of a multispecies model, from top-down to bottom-up (Walters and Martell in review).

Fourth, forecasts usually assume that some management scheme will be in place in the future. In reality, there is substantial uncertainty about future management decisions and the degree of compliance with management regulations. Although this could be considered part of model uncertainty, institutional uncertainty brings into play a higher order of complexity associated with forecasting how society and its institutions will behave in response not only to the vagaries of natural systems but also to economic, social, and political forces.

Different forecasting approaches have different capacities for dealing with uncertainty. Modern single-species forecasts usually incorporate uncertainty in initial conditions, process uncertainty, and parameter uncertainty using Bayesian techniques. Structural uncertainty is commonly treated in a more ad hoc way, by conducting forecasts using a small number of alternative model structures when searching for robustness in policy performance (e.g., Butterworth and Punt 1999). Less frequently, formal Bayesian techniques are used to estimate the plausibility of alternative model structures (e.g., Patterson 1999; McAllister and Kirchner 2002; Parma 2002a).

Multispecies models of intermediate complexity, like those derived by extending single-species models to account for predation effects, facilitate the incorporation of current state-of-the-art tools used in single-species models. When it comes to large multispecies approaches, uncertainties that surround model forecasts are much less frequently conveyed. For example, uncertainties about input parameters to Ecopath can be explored using the ECORANGE routine, but the sensitivity of Ecosim predictions to these uncertainties is often overlooked. Walters and Martell (in review) recommend the use of alternative values to partition predation mortalities, in addition to those implied by diet composition data, to evaluate sensitivity with respect to uncertainty in the data. Despite similar warnings repeatedly made by modelers (Aydin and Friday 2000; Walters et al. 1997), the software has often been often used as a black box.

4.8.2.2 Strengths and Weaknesses of Different Approaches

The merits and limitations of the different forecasting approaches need to be viewed in the context of the purpose of the forecasting exercise—that is, what question is being addressed. Single-species approaches continue to be the preferred approach for evaluating the performance of single-species management procedures. Their main strength is that they are formally conditioned on past data (which means management draws its lessons from history). The methods for doing this are supported by a significant development of statistical techniques (and specialized software) for estimating model parameters efficiently, quantifying uncertainty based on modern Bayesian techniques, and incorporating this uncertainty in decision analysis. Their limitations are mainly a function of the quality of the data used for model fitting and the peculiar history of exploitation of the stock in question.

In many cases, stock assessments, and in turn population forecasts, rely solely on fishery-dependent data. This is problematic because there are many ways in which catch per unit of effort may fail badly as an index of stock abundance (Hilborn and Walters 1992). Also, many exploitation histories correspond to depletion trajectories, the so-called one-way trips (Hilborn and Walters 1992), which do not provide needed contrast in abundance and effort, making it hard to distinguish productivity and mortality parameters when conditioning on past data. Conditioning is so critical because by fitting a model to historical data before attempting a forecast, we demonstrate that the model is able to reproduce historical trends and we constrain the universe of possible models. This, however, is no guarantee that the model will be able to extrapolate system responses correctly to novel perturbations in the future.

Aside from these limitations, single-species approaches obviously cannot be used to address ecosystem questions, such as forecasting the impact of large-scale perturbations or determining how human interventions propagate from particular components to the rest of the ecosystem. Some multispecies concerns, such as the impact of a given single-species management procedure on other species, may best be addressed by modeling only the linked dynamics of the key species involved, as in the "minimal realistic model" of the hake-seal system developed by Punt and Butterworth (1995). The uncertainty present in single-species models is here compounded by uncertainty in the parameters and relationships that govern species interactions. This increase in model uncertainty was the main reason why the large multispecies approaches developed in the late 1970s and early 1980s fell out of favor (Quinn in press).

The resurgence of multispecies models, such as MSVPA in the North Sea and the Bering Sea, was accompanied by major investments in field programs of stomach data collection to help fill some of the information gaps. Unfortunately, such investments are seldom possible, so lack of basic data to support multispecies models will be a major limitation for their widespread use.

Beyond observation uncertainty, other problems detected when using top-down multispecies models to forecast ecosystem changes seem to reflect limitations of the basic core assumptions used to represent predator-prey interactions. MSVPA, for example, assumes that the predator is always able to consume a fixed ration of food. According to Walters and Martell (in review), forecasts done using top-down multispecies models based on the mass-action principle have produced some unrealistic results (such as strong trophic cascades, loss of biodiversity, and dynamic instability) more drastically and more frequently than is supported by field evidence.

The development of the foraging arena concept of Ecosim as an alternative to mass-action assumptions was a major step forward, allowing control of the degree to which the model behaves as top down or bottom up. However, choosing appropriate values for prey vulnerability parameters is difficult due to the lack of information to quantify these processes (Plagányi and Butterworth in review). The alternative of using default values followed in many applications is unsatisfactory, as Ecosim predictions are highly sensitive to the choice of vulnerability settings (Shannon et al. 2000). Further development of time series–fitting approaches and alternative estimation schemes will be needed to help parameterize these processes. Some alternatives are discussed by Walters and Martell (in review).

Like the foraging arena formulation, the implications of several other assumptions in Ecosim are just beginning to be explored (see detailed discussions in Aydin and Friday 2000; Christensen and Walters 2000; Plagányi and Butterworth in review; Walters and Martell in review). In particular, the assumption of mass balance and the use of Ecopath as a starting point have raised criticism. On the one hand, the mass balance condition is a strength in that information is added by forcing the productivity of all consumers to be supported by primary productivity in the ecosystem. This is in sharp contrast to Lotka-Volterra systems, where the overall productivity is unconstrained, leading to instability.

This information, however, is not without a cost. First, it augments the requirements for ecosystem-wide data, including primary production, and specification of the form of functional responses in predator-prey relationships among all functional groups represented. Second, reliance on Ecopath biomass flows balanced for some reference time implies that predator-prey parameters are time-invariant, which may not hold when the ecosystem changes substantially from the reference situation. The assumption of equilibrium commonly made when balancing Ecopath equations may be even more problematic when biomass of some of the key groups is changing during the reference time (Walters et al. 1997; Plagányi and Butterworth in review).

To conclude, single-species approaches will be hard to beat as tools for describing the dynamics of exploited stocks. Improvements on predation mortalities may result from incorporation of multispecies interactions but only when the data required to parameterize them are available. Large multispecies models such as MSFOR and Ecosim, on the other hand, have been and will be useful to explore ecosystem function and to postulate alternative scenarios about plausible ecosystem responses to environmental change and human interventions, when applied taking due care of uncertainties and potential pitfalls. To date, calibration and diagnostic methods and expertise have not yet advanced to the standards common in single-species fishery models. The value of these approaches to guide management decisions in the future will be a direct function of the expertise gained in that area.

None of the forecasting tools should ever be used without at the very least exploring the sensitivity of predictions to alternative model parameterizations and observation uncertainties. This is less of a problem in single-species fishery forecasting because assessment scientists have learned (the hard way) not to trust model predictions, and growing emphasis is placed on robustness and precaution. The risk is more serious with multispecies powerful packages like Ecopath with Ecosim, which are relatively easy to set to run without careful consideration of the implications of default choices.

4.8.3 Research Needs

In general, it can be argued that fishery models must be unsuccessful because such a large portion of fishery stocks have been overexploited, and some have even collapsed. In many of these cases, however, the collapse of the stocks was anticipated by the models (of, for example, Georges Bank cod). Thus it is not clear what is a failure of modeling and what is a failure of policy-making.

Improved understanding of ecosystem function and improved forecasting capabilities will require research and developments in several fronts, including:

- research aimed at improving understanding of spatial structure and relevant scales at which different natural processes operate and at evaluating when is it worth the effort to incorporate the space dimension into single or multispecies models and collect the required data;
- development of approaches to bridge the gap between detailed process-oriented studies and simpler empirical models useful for fisheries forecasting (can we use the results of process-oriented studies to build alternative scenarios, represented as simple model prototypes, and assign relative plausibility?);
- further development and testing of formal approaches for conditioning ecosystem models to different sources of information, including times series data;
- development of new methods for estimating predator-prey vulnerability parameters; and
- further exploration of the implications of core assumptions made in ecosystem models and consideration of alternative formulations.

4.9 Forecasting Impacts on Coastal Ecosystems

Ecological forecasts predict the effects of biological, chemical, physical, and human-induced changes on ecosystems and their components. Short-term coastal ecosystem forecasts, such as predicting landfall of toxic algal blooms, are similar to those done for weather and hurricane prediction, which also affect human well-being. On the other hand, forecasting large-scale, long-term ecosystem changes has similarities with macroeconomic forecasts that rely heavily on expert judgment, analysis, and assessment, in addition to numerical simulation and prediction. Forecasts of such broad-based, long-term effects are particularly important because some of the most severe and long-lasting effects on ecosystems may result from chronic influences that are subtle over short time frames. In this sense, one aspect of coastal forecasting has a longer history because of the well-developed use of modeling in fisheries stock assessments, as described in the preceding section.

Coastal ecosystem models should be able to predict long-term changes in ecosystem function based on past and present environmental and societal change and on coastal governance processes. The results of such a model will depend not only on the modeling of physical, chemical, and biological spatial and temporal data but also on the value judgments involved in the decision-making process. The key direct drivers of coastal ecosystem change that may affect human well-being and that are a priority for coastal forecasting are eutrophication, habitat modification, hydrologic and hydrodynamic disruption, exploitation of resources, toxic effects, introduction of non-native species, global climate change and variability, shoreline erosion and hazardous storms, and pathogens and toxins that affect human health.

4.9.1 Existing Approaches

The basic structure of a simple coastal forecasting model consists of a meta-data portal linked to an analysis system. The meta-data portal is an algorithm that integrates and manages data from many disparate sources and organizes them into a form that can be used by the analysis system. Data can be from archived sources or arrive in real time from satellites and onsite measuring instruments. The analysis component that processes the physical, chemical, and biological data required to monitor the direct drivers is normally handled by a set of interactive deterministic multimodels, the choice of which depends on the questions being asked. Interactive or coupled multimodels consist of a set of stand-alone models that handle different kinds of data (such as in situ optics, chemical analyses, and remotely sensed data) and that communicate with each other in order to predict the likelihood of some outcome (such as a harmful algal bloom). Final output is usually in the form of a visual display in a GIS or mapping module.

Deterministic models are commonly of two types: empirical models based on observation or experience in particular places and mechanistic models based on theories, which explain phenomena in purely physical terms. Empirical models are very common but of limited general use and are not discussed further. What we need instead are models that can accommodate the value judgments involved in the decision-making process of humans. For this, some sort of decision support system is required. The current state of the art is still a long way from integrating this latter aspect into existing coastal forecasting systems, which at present do not allow sufficient lead time for coastal managers to intervene in order to avert a potentially undesirable long-term outcome. This assessment is not meant to review the many excellent scientific publications on coastal models. It aims rather to give a sense of the state of the art in relation to the aspiration of building scenarios that inform the decisions of coastal managers for long-term planning.

4.9.1.1 Nowcast/Forecast Modeling Approach

A nowcast/forecast type system results when data from multiple sources is fed to a meta-data portal in real time. The term "nowcast" is used because it refers to the fact there is no lag time between events and analyses—data are immediately fed into the decision analyses. Nowcast models are of interest because they promise the possibility of allowing scenarios over long time scales to respond to discontinuities and surprises as they arise. The Global Ocean Observing System has scientific details of the operation of a nested set of regional coastal and ocean forecasting systems (see http//: ioc.unesco.org/goos).

An illustrative state-of-the-art example of a regional nowcast/forecast system is the New Jersey Shelf Observing System being developed by the Coastal Ocean Observatory Laboratory. The aim is to provide a synoptic 3-D picture of the biogeochemical cycling of elements and physical forcing of continental shelf primary productivity in the New York Bight (Schofield et al. 2002). The system under development consists of an array of surface current radar systems, color satellites, and autonomous underwater vehicles. These will input mainly bio-optical data into a new generation of physical-biological ocean models for hindcast and real-time continental shelf predictive experiments. Results will be disseminated in real time to both field scientists and water quality forecasters over the Internet (marine.rutgers.edu/cool) as well as to the general public (www.coolroom.org).

The ensemble of forecasts is generated by an extensive suite of atmospheric, ocean, and biological models including ROMS–the Regional Ocean Modeling System and TOMS–the generalized Terrain-following Ocean Modeling System. ROMS is interfaced with a suite of atmospheric forecast models. TOMS is coupled with a bio-optical ecosystem model, which uses the spectral distribution of light energy along with temperature and nutrients to estimate the growth of phytoplankton functional groups representing broad classes of the phytoplankton species. The biological forecast can then be validated in real time from the field measurements that can guide the evolution of the model. Errors between the model prediction and the field measurements are used to direct autonomous underwater vehicles into regions where more data are needed.

4.9.1.2 Decision-Support Approach

Another approach is to supplement deterministic models by decision-support techniques. Decision analysis is a step-by-step analysis of the consequences of choices under uncertainty. Decision-support techniques include cost-benefit analysis, cost-effectiveness analysis, multicriteria analysis, risk-benefit analysis, decision analysis, environmental impact assessment, and trade-off analysis. Of the various decision-support techniques in use, only multicriteria analysis uses mathematical programming techniques to select options based on objective functions with explicit weights, which stakeholders can then apply. The other approaches are not easily adaptable to mathematical programming techniques because of lack of clear techniques for incorporating information in the decision-making process.

SimCoast provides an illustrative example of how a fuzzy logic expert system can be objectively programmed into a coastal ecosystem decision-support model. According to McGlade and Price (1993), three key intelligent systems techniques potentially useful for sustainable coastal zone management are neural networks, expert systems, and genetic algorithms. However, interactions between these methods and other approaches such as fuzzy logic and issue analysis also give users the ability to assess the combined uncertainty and imprecision in their knowledge and data.

SimCoast is a fuzzy logic, rule-based, expert system in which a combination of a fuzzy logic and issue analysis has been used to produce a soft intelligence system for multi-objective decision-making. It is designed to enable researchers, managers, and decision-makers to create and evaluate different policy scenarios for coastal zone management. The conceptual basis is a two-dimensional multi-zoned transect onto which key features such as ports, laws, mangroves, and activities such as fisheries, aquaculture, shipping, and tourism are mapped. These activities are associated with different zones and with the process to which they are linked (such as land tenure, erosion, organic loading). The effects of activities on the features are evaluated in relation to defined policy targets (water quality, system productivity, ecosystem integrity, for instance) measured in particular units (oxygen level, turbidity, *E. coli* concentrations, number of species, or biomass). This evaluation is the result of consensual expert rules defined during workshops. Fuzzy logic and certainty factors are used to combine new data and build scenarios based on the ideas or even alternative hypotheses of experts.

4.9.2 Critical Evaluation of Approaches

4.9.2.1 Nowcast/Forecast Modeling

There are numerous coastal ecosystem nowcast/forecast systems based on deterministic models coupled to a GIS to predict harmful algal blooms, oxygen depletion effects, oil spills, climate change effects, and the like. In spite of their great scientific interest, these approaches require considerable expertise and resources that are not widely available to coastal ecosystem managers around the world. Further, each coastal area has different conditions and priority problems, so that no single system of deterministic models will be useful in most situations.

Coastal nowcast/forecast systems are typically dominated by uncertainties in model initialization largely attributable to under-sampling. To deal with this, an ensemble of forecasts with differing initial conditions is used to identify regions in which additional data are required (Schofield et al. 2002). Hence the models provide insight into what has not been sampled and guidance for further real time observational updates using multiple platforms, including remote (satellites, aircraft, and shore-based), stationary (surface and subsurface), movable (ships and autonomous underwater vehicles), and drifting (surface or vertically mobile) systems.

This rapid environmental assessment capability changes the entire paradigm for adaptive sampling and nowcast/forecast modeling. Forecast errors or misfits may now be dominated by uncertainties in the model formulations or boundary conditions, and ensemble forecasts with differing model parameterizations identify regions in which additional data are needed to keep a model on track. In the time it takes to prepare the ensemble of forecasts for the well-sampled ocean, additional data have arrived, and on-the-fly model-data metrics can be used to quantify which forecast in the ensemble is the least uncertain (Schofield et al. 2002). This approach offered the MA the potential to have scenarios and long-term forecasts dynamically updated to adapt to discontinuities and surprises, which are an increasingly common feature of the modern world.

4.9.2.2 Decision Support Systems

Decision support techniques are not really forecasting methods. They do, however, provide a structured framework through which a choice between alternatives can be made with regard to a given set of criteria. This more widely accessible approach can be criticized for theoretical difficulties associated with aggregating preferences for use as weights in the models.

Expert systems, by their very nature, deal with a good deal of uncertain data, information, and knowledge. Decision support systems use many methods to integrate uncertain information for inference: these most commonly include Bayes theorem or the Dempster-Shafer theory of evidence, but certainty factors and fuzzy sets are sometimes also used. The commonly used Dempster-Shafer theory of evidence (Dempster 1968; Shafer 1976), which is an extension of Bayes theorem, appears to be a robust approach. According to Moore et al. (2001), this theory does not require exhaustive prior or conditional probabilities before calculation can take place, and it can be used where evidence is based on vague perceptions or entirely lacking.

Normally, where probabilities are not known, equal prior probabilities are unrealistically assigned to each competing piece of evidence, and the sum of all assigned probabilities must equal one. With the Dempster-Shafer theory, an ignorance value close to zero (ignorance = 0 represents complete ignorance) can be used to represent the lack of information, rectifying what would be erroneous with probability. Related to this is the fact that when belief is assigned to a particular hypothesis, the remaining belief does not necessarily support the hypothesis' negation. Other advantages of using the Dempster-Shafer theory include the ability to use evidence supporting more than one hypothesis (a subset of the total number of hypotheses). Finally, this approach models the narrowing of the hypothesis set with the accumulation of evidence, which is exactly how experts reason. It held the possibility for the MA to allow fully specified uncertainties being attached to scenarios. It creates a feedback loop, which stimulates human beings to take decisions that they think may change the scenario outcome.

4.9.3 Research Needs

Traditional ecological forecasting and decision-support methods are no longer adequate because they have a limited ability to predict discontinuities—significant nonlinear changes in the direct or indirect drivers of change that force a fundamental re-evaluation of strategy or goals. We therefore need to look for new models that are able to accommodate discontinuities and facilitate proactive scenario planning where the past is an increasingly unreliable guide to the future.

Perhaps the deliberative process that attempts to look at the long-term future of ecosystems advocated by Clark et al. (2001) and adopted by the MA should advance beyond conventional ecological forecasting and be more accurately referred to as ecological foresighting. This is taken to mean not the identification of the most likely scenario but the evaluation of many possible, feasible, or even desirable scenarios. This helps develop a deeper understanding of the options and promotes better planning from a backcasting standpoint. Since long-term ecological foresighting must have as a base significant hindcast and nowcast information, both nowcast/forecast deterministic models and scenario-based decision support systems need to be linked so that relevant up-to-date alternatives are presented to coastal managers.

We need to also develop ways of modeling and of estimating how ecosystem services respond to combinations of stresses at local and regional scales. The combination of complex interactions among a large number of components with the variable nature of ecosystems and their driving forces makes the development of such tools a significant challenge. Potential techniques include neural nets, artificial intelligence, fuzzy sets, and massively parallel algorithms.

4.10 Forecasting Impacts on Human Health

Forecasting the impacts of future ecosystem change on human health (McMichael et al. 2003) at a global scale and over the next century is daunting. This task is subject to such large uncertainty that it might reasonably be considered impossible, or at least not scientific. Nevertheless, uncertainty is not infinite, and many boundary conditions can be identified. These include not only the consistency of anatomy, physiology, and pathophysiology (disease processes), but also the fact that social and technological factors will continue to influence and modify human health, as they have for millennia. Though substantial uncertainty remains about the characteristics of even present health at the global scale, a great deal is known.

4.10.1 Existing Approaches

One dominant approach to modeling human health and disease is embodied by classical epidemiological and bioclimatic treatments of malaria, and even wildlife disease (e.g., Dobson 2000; Rogers and Randolph 2000). These approaches typically start with a detailed look at one disease and one host, and then build toward predictions of critical thresholds for epidemics and the implications for public policy. Land changes or climatic changes are especially important when the diseases are transmitted by vectors, such as malaria being transmitted by mosquitoes; this is because temperatures alter vector survival and behavior, and land alterations can create or destroy habitats for vectors. Because they are host-pathogen specific, these approaches do not lend themselves easily to global assessments; nor are they motivated toward global assessment, since health policy is often formulated one disease at a time. Currently, there is a move away from modeling one species at a time—even from the perspective of classical epidemiology. For instance, there is a growing recognition that climatic and habitat perturbation may underlie the emergence of many new human diseases (Patz et al. 1996), but no models of this process are yet available.

Because of the limitations of single-species disease models, an alternative emphasis for global assessments has been on a more phenomenological or aggregate approach that emphasizes connections between population demography, social behavior, and poverty. This topic can appear overwhelmingly complex. It may be useful to consider that uncertainty applies to three key ''black box'' determinants relevant to this task. These boxes can be conceptualized as input, output, and modifying determinants, where input represents the state of ecosystems, output the state of health, and modifiers the social, technological, and political cofactors that can either dampen or exacerbate the importance of ecosystem change upon health. Of course, in reality these categories are not clearly separate. At all times, a continuous interaction exists between these three categories, though often the causal links are subtle, poorly identified, and at least in some cases—away from thresholds—unimportant.

Clearly, myriad possible interactions and cascading responses between ecosystem services, human health, and the societies and institutions that modify and influence both health and ecosystems are possible. The outcomes can be positive or negative. One method has been proposed to classify potential adverse responses into one of four broad groups, called ''direct,'' ''mediated,'' ''modulated,'' and ''systems failure'' effects (Butler et al. in press).

In this categorization, direct health effects manifest through the loss of a useful ecosystem service, such as the provision of sufficient food, clean water, or fertile soil or the restriction of erosion and flooding. Direct effects occur as the result of physical actors but do not include pathogens per se. They are probably the most easily understood of the four effects.

Mediated effects, as opposed to direct ones, have increased causal complexity and in some cases involve pathogens. Some have potentially high morbidity and mortality. There is also often a longer lag between the ecosystem change and the health outcome than for direct effects. Many infectious and some chronic diseases fall in this category. In many of these cases disease have emerged as a result of the increased food-producing capacity of ecosystems (a provisioning ecosystem service)—for example, by animal domestication, irrigation, dams, and other intensive farming practices. A trade-off has been the unforeseen increase in the incidence and prevalence of many of these communicable diseases.

Effects called ''modulated'' and ''systems failure'' have also been identified as larger-scale, more lagged, and more causally complex adverse consequences of ecosystem change. Modulated effects refer to episodes of state failure or of nascent or realized large-scale social and economic collapse. Systems failure refers to economic and social collapse at a supra-national scale as a result of coalescing, interacting modulated effects.

This classification can be mentally fitted to different ecosystem futures. For example, if a region experiences marked loss of provisioning services, then direct adverse effects, such as the disruption of flooding or increased hunger, are likely. Loss of biodiversity, and more contact between humans and undomesticated species may mean the occurrence of more mediated effects, including emerging infectious diseases. Greater intensification of animal husbandry may facilitate the spread of recombinant forms of known diseases, such as influenza. However, more realistic and useful predictions of the health impact of ecosystem change require greater understanding and at least attempted predictions of the social, institutional, and technological factors that modify health—the third of the black boxes identified earlier.

In some cases, such as modulated health effects, health itself may critically affect the quality of these human services. It is true that modulated effects are far less likely to occur in societies that have strong institutions, reasonable governance, and high technology. Adverse health effects consequent to ecosystem change and reduced ecosystem services may in some cases overwhelm societies that are already fragile, however, causing them to exceed a ''tipping point'' beyond which decline is highly likely.

Although far less likely, it is also possible to envisage pathways and causal webs that test the social, economic, and health fabrics of societies that currently appear almost invulnerable to adverse ecosystem change. For example, an interlocking cascade of adverse events and erroneous decisions led in the last century to the Great Depression and World War II. Although perceived resource scarcity was a factor in this cascade (for example, in both the German and Japanese peoples' desire for expansion), ecosystem buffers—especially on a per capita basis—were far higher then than they are now.

4.10.2 Critical Evaluation of Approaches

Conventionally, scenario theorists accentuate and extrapolate existing trends into the future, imagining and modeling how different futures will unfold. One problem with the scenario approach is that assumptions about the future are typically ''bundled together,'' as in ''TechnoGarden,'' whereby across-the-board technical innovation is expected to meet global challenges. But an imaginary future marked by rapid technological progress may adversely affect human health if it is not also accompanied by other forms of progress. That is to say, affordable vaccines, surgery, and pharmaceuticals may not be fully able to compensate for poor health if high technology is also accompanied by a dehumanization of society.

Second, human health is a mix of technology, environment, and social systems. Predicting how these interlink is almost impossible, and we lack both theory and empirical relationships as guidance. We have studies that predict how climate variability might directly affect human health through air pollution and diseases (McMichael et al. 2003), but the fact that climate change will also alter distribution of wealth and disrupt societies is not factored into these health predictions.

Reductionist approaches to science have sought to simplify and analyze reality by considering isolated elements, and at ever finer resolution. This approach has been very successful in many fields and has contributed substantially to the enormous scientific, technological, and material progress that marks our time. And although material progress is not sufficient for either human health or human well-being, it is clearly an important contributor to both. Yet reductionist methods have limits that are increasingly recognized. A major drawback is that they mask the significance of threshold effects and, even more important, they can actually hide the concept of thresholds.

In a linear, reductionist conceptualization of reality, an increment of change is not of itself very important. If the experimenter (including the unwitting social and ecological experimenter) concludes that an increment of change causes an undesirable increment of response, then linear thinking suggests that the remedy is simply to subtract that increment. In many cases this is possible. In ecosystems, society, and human health, however, innumerable though still poorly defined thresholds exist beyond which reversal is either impossible or prohibitively expensive. This phenomenon of costly or impossible reversibility, also known as hysteresis, is increasingly recognized in ecology (Scheffer et al. 2001a), but has as yet been little studied in relation to health and society (Butler et al. in press).

4.10.3 Research Needs

The critical areas of research entail linking together the many threads that affect human health. We still lack some of the most basic information on how the epidemiology of disease is altered by the environment. Inevitably, human systems respond to health threats, and any sort of prediction regarding possible adaptive responses is totally lacking in global health projections. We know historically that the collapse of social systems can drastically affect human health. Systems failure, were it to occur, is possible as the century unfolds. Yet we have very little ability to predict or anticipate these system failures, which in turn put so much stress on health care systems.

There may be many opportunities for translating the successes of specific epidemiological models into true global assessments. The situation now is very much like that of ecology 30 years ago, when the focus was on single-species models or models of pairs of interacting species. The rise of ecosystem science and attention to biodiversity prompted a whole new generation of models, but still with critical ecological underpinnings. Global health assessments would benefit from attempts at using epidemiological models to scale up and aggregate over many diseases toward summary predictions.

4.11 Integrated Assessment Models

Many environmental problems are caused by a complex web of causes and effects that have environmental, social, and economic dimensions. The fact that these webs cannot be well described by disciplinary approaches has led to an increasing interest in integrated assessment models. Weyant et al. (1996), Van der Sluijs (1997), Rotmans and Dowlatabadi (1998), and Toth and Hizsnyik (1998) provide interesting reviews of integrated assessment definitions and methods. In general, they describe IAMs as modeling frameworks to organize and structure various pieces of (disciplinary) scientific knowledge in order to analyze the cause-effect relationships of a specific problem. The analyses should have a wide coverage and include cross-linkages and interactions with other problems.

The term IAMs is applied in particular to models that include some description of the socioeconomic system (including economic activities and human behavior, population dynamics, and resource use) and its interaction with the environmental system (regional air pollution, the climate system, land cover/land use, and so on). They can be qualitative (conceptual models) or quantitative (formal computer models). IAMs are used to synthesize available scientific information from different disciplines, and their specific approaches and assumptions, in an organized way. An essential feature of IAMs is their focus on application for policy support and on assessment rather than scientific research per se. In such policy-oriented applications, IAMs have different functions. They serve as an early warning system and an exploration of possible futures, they are used for policy evaluation, and they provide tools that directly support public decision-making and negotiations.

IAMs can be categorized in various ways. A first classification is the dominant modeling paradigm. IAMs can be calculated as either simulation or optimization models. Most simulation IAMs are based on differential equation descriptions. Sometimes partial optimization is used. The IAMs derived from an economic problem setting tend to use optimization techniques to evaluate the minimum cost or other objective function of certain trajectories. These types of IAMs are like dynamic cost-benefit analyses. Within both modeling paradigms, deterministic as well as stochastic approaches are used, although the former dominate. Within optimization IAMs, a further distinction can be made according to the degree to which the objective is to satisfy exogenous constraints or targets.

A second classification concerns horizontal and vertical integration. Vertical integration refers to the degree to which a model covers the full cause-effect chain of the relevant issue—from driving forces to pressures, to changes in state, to impacts, and finally to possible responses. Vertical integration has emerged from the pressure-state-impact-response framework in environmental policy. Horizontal integration refers to the integration between different aspects of the object of study. This can be in a rather narrow sense, such as integrating the interactions between water and land cover/land use, or much wider, as in the integration of demographic/health issues and the state of the environment. A related classification is in terms of the topic they focus on. This is often a reflection of the intended policy application. Many IAMs have been used to explore the dynamics of acidifying pollutants and greenhouse gases and their impacts. To make IAMs policy-relevant, cost modules and allocation algorithms can be added.

As with other models, IAM outcomes depend strongly on the assumptions made. As IAMs often cover a broad range of different topics and focus on integration of disciplinary knowledge (scientific information on the linkages among different disciplines is often less "strong" and involves more expert assessment), these assumption play a more important role than in other areas of modeling. In IAMs dealing with climate change, for instance, key uncertainties include developments of population and economy, sociopolitical choices with respect to human development (such as environmental policies), technology development, and discount rates. Several tools have been developed to deal with uncertainties. An important tool includes the use of storyline-based scenarios, defining consistent sets of assumptions. Others include more traditional uncertainty analysis and the assignment of qualifications to uncertain model outcomes (see, for example, www.nusap.net).

Almost by definition, the field of IA modeling is rather broad and vaguely defined. One reason for this is that it is relatively new, and universal rules and principles have not yet crystallized. This makes the overview in this section rather eclectic and limited, focusing on specific examples. We do not intend to give an extensive overview of all available models in the field. For many specific applications, such as integrated assessment of climate change, comprehensive overviews already exist (Weyant et al. 1996; Rotmans and Dowlatabadi 1998). We confine ourselves to models with a relatively large level of integration that have not yet been covered in other sections of this chapter.

4.11.1 Existing Approaches

IAMs first became popular in the fields of air pollution control and climate change. The work in these areas in the late 1980s and during the 1990s generated several models that are useful for carrying out assessments in global environmental change or sustainable development because they have typically both a long time horizon and a global perspective. For example, UNEP's *Global Environment Outlook* (UNEP 2002) and IPCC's *Special Report on Emissions Scenarios* (Nakićenović and Swart 2000) have all built on these models.

The first well-known IAM was built in the early 1970s in response to the concerns about world trends of a group of industrialists and civil servants, the Club of Rome (Meadows et al. 1972). The computer simulation model World3 described couplings between the major demographic, resource, and economic components of the world system at the global level. It used the system dynamics method developed at the Massachusetts Institute of Technology from electrical engineering science. Its main purpose was to raise awareness about the nature of exponential growth in a finite world and the systemic nature of the observed and anticipated trends due to the various linkages between what were at the time largely seen as separate processes. It showed the risks in continuing business-as-usual development paths—so much so that only its doomsday message came across. This model, and subsequent efforts at more disaggregated models (e.g., Mesarovic and Pestel 1974) inspired the development of a whole set of derived models. It also started a vigorous debate about the nature of market processes, which according to most economists would solve most problems long before a catastrophe would unfold.

A second generation of IAMs had a more narrow focus on a particular environmental problem and the ways in which policy could deal with it. This was partly in response to the aggregate nature of the first generation models that made it hard to perform meaningful validation and policy support. An outstanding and well-known example in this respect is RAINS—the Regional Acidification Information and Simulation model of acidification in Europe developed in the 1980s (Alcamo et al. 1990). It played and still plays a major role in the international air pollution negotiations in Europe.

The first steps of IAMs dealing with the causes and consequences of climate change were taken in the late 1970s. Examples include models by Nordhaus (1979) and Häfele et al. (1981), although the environmental part in these examples was extremely simple, including only atmospheric CO_2 concentration. Mintzer (1987), Lashof and Tirpack (1989), and Rotmans et al. (1990) extended these models by including more physical and chemical aspects of the climate system. Since then, a large number of such models have been developed and currently more than 50 climate change-oriented IAMs coexist (Van der Sluijs 2002). More recently, IAMs have been developed with an expanded or different emphasis, such as water (e.g., Döll et al. 1999) and human health (Martens 1997). In the community of economists, the emphasis has been on the merging of a neoclassical economic growth model with a simple climate system model and on using it in the search for cost-effective abatement strategies. Here, too, a series of additions has followed, such as a more elaborate energy system, more in-depth treatment of technological dynamics, and integration with impact modules.

As these third-generation IAMs are expanding their scope and level of integration, they are slowly developing from environmental or climate change models into global change or sustainable development models. (See Table 4.1.)

4.11.2 Critical Evaluation of Approaches

Three evaluation criteria were developed for discussing IAMs in the context of quantifying the MA scenarios:

- Is there any integration between ecosystems and other parts of the (world) system, such as land, water, atmosphere, population, and economy, and if so, how is it done?
- At what spatial and time scale(s) are the ecosystem and the interactions with other parts modeled, ranging from short-term local dynamics to large-scale and global long-term dynamics?
- To what extent is the model used, or has it been used, for policy applications, and if so, how is the interface with decision-makers or analysts constructed and applied?

For our purpose, we clustered three groups of IAM models. The first group contains models that have been built with the explicit objective of providing an integrated insight into a broad range of environmental, economic, and social aspects of sustainable development. The second group contains models that have been mostly built around the link between economic development, the energy sector, and the climate system. The third group of models is a subclass of the previous one. These models started out as energy-environment models but have evolved to a point where the newly developed ones are now better characterized as a third category: global change models. (We have not included the IAM models on regional air pollution control here because of their narrow focus. It should be noted, however, that the RAINS modeling team is currently extending its framework to cover not only acidification, eutrophication, and ground-level ozone but also greenhouse gas emissions.)

4.11.2.1 Sustainable Development Models

This group of IAMs has the highest level of integration in terms of social, economic, and environmental issues. In order to avoid levels of complexity that are too large, they use a rather high level of aggregation. They use expert-model derived meta-level descriptions of underlying processes—often correlations or ''stylized facts''—and a low level of spatial or regional disaggregation. This group includes the system-dynamics World3 model and the more recent related models such as International Futures (Hughes 1999), TARGETS (Rotmans and De Vries 1997), Threshold 21 (Barney 2000), and GUMBO (Bouwmans et al. 2002). It also includes the Polestar system, which systematically links scenario assumptions and scenario outputs for a wide range of issues (Raskin et al. 1999).

Consistent with their high level of aggregation, most of these models try to answer rather broadly formulated questions, identifying possible trade-offs between economic developments and ecological functioning without providing detailed and concrete strategies or policy advice on how to deal with the trade-offs. From the perspective of developing scenarios for ecosystem services, the TARGETS model, the Polestar model, and the GUMBO model have provided interesting insights. In the context of the MA, these models had major advantages of allowing for a high level of integration and of including several feedbacks. Their description of detailed (ecological) processes is often simple, however.

The TARGETS model (Rotmans and de Vries 1997; De Vries 2001) has been developed at the Dutch National Institute of Public Health and the Environment and applied to work out three consistent perspectives on sustainable development. It includes five submodels, one of which simulates key biogeochemical cycles. The land cover/land use and the food, water, and energy supply-and-demand dynamics are simulated at an aggregate level. Scenarios were built around the framework of the Cultural Theory (Thompson et al. 1990), with an evaluation of parameter assumptions and model outcomes in terms of ''utopian'' and ''dystopian'' courses of events. The model allows a clear linkage with ecosystem services at the high aggregation

Table 4.1. Examples of Integrated Assessment Models (Adapted from Bakkes et al. 2000)

Model	Analytical Technique	Horizontal Integration[a]	Vertical Integration[b]	Key References	Key Existing Scenarios	Ease of Use by Non-Developers[c]
World 3	system dynamics	present	limited	Meadows et al. 1972; Meadows et al. 1992	13 explorative scenarios	limited
Int. Futures	system dynamics	advanced	limited	Hughes 1999	base scenario	very high
TARGETS	system dynamics	present	present	Rotmans and de Vries 1997	reference case with varieties	high
Threshold 21	system dynamics	advanced	present		several explorative scenarios	very high
Polestar	accounting	present	limited	Raskin et al. 1999; SEI Boston Center 1999	SGS-scenarios	very high
MESSAGE	dynamic linear programming	limited	limited	Messner and Strubegger 1995; Riahi and Roehrl 2000	SRES, WEC	limited
MiniCAM	partial equilibrium	limited	limited	Edmonds et al. 1996	SRES	high
AIM	general equilibrium	limited	limited	Morita et al. 1994	SRES, GEO	limited
IMAGE	system dynamics/ simulation	limited	advanced	Rotmans 1999; Alcamo 1994; IMAGE-team 2001	SRES, GEO	limited

[a] Very limited indicates a lack of integration between domains as well as within a domain. Limited refers to a lack in one of the two. Present indicates several domains are covered in an integrated manner. Advanced is used for models that include environmental, economic, and sociocultural aspects.

[b] Limited refers to models where several parts of the cause–effect chains modeled are missing or not explicit. Present refers to the models where the casual chain is modeled, but there is a lack of feedback from the output of the model to the input. The term advanced is reserved for models where this final loop is also closed.

[c] Very limited refers to models that are not accessible to non-developers. Limited refers to models where the models can be used by outsiders after considerable training. The term high classifies models that exhibit an interface and a level transparency that makes it very easy for non-developers to apply the model and to adjust it to their own needs.

level used. In contrast to most other global models, the TARGETS model included a full link back from environmental change into demographic developments (including health) and a partial evaluation of feedbacks upon the economy. The main disadvantages of the TARGETS model are the lack of regional disaggregation and the fact that, like most IAMs in this group, it was not related to a specific decision-making process.

Polestar is an integrated accounting framework developed by the Stockholm Environment Institute's Boston Center (SEI Boston Center 1999). Its best known application has been in conjunction with the Global Scenarios Group (Gallopin et al. 1997). The backbone of the model is an extensive data set containing a wide range of social, economic, and environmental variables. Polestar has relatively little relationships between each of the variables in the system. In that sense, it is not so much of a model as an accounting framework to explore various assumptions. It is more suitable for exploring the range of possible futures and the possible impact of certain policy interventions than for deriving integrated and balanced answers for issues related to political decision-making. Polestar has been very successfully applied in supporting various scenario development processes with strong user involvement, including scenarios that describe some elements of ecological functioning.

Finally, the GUMBO (Global Unified Metamodel of the Biosphere) model was developed explicitly to deal with a description of ecological services and their possible future development under various assumptions (Bouwmans et al. 2002). It is a ''metamodel'' in that it represents a synthesis and a simplification of several existing dynamic global models in both the natural and social sciences at an intermediate level of complexity. GUMBO includes dynamic feedbacks among human technology, economic production, and welfare and ecosystem goods and services within the dynamic Earth system. It includes modules to simulate carbon, water, and nutrient fluxes through the environmental and ecological systems. GUMBO links these elements across eleven biomes that together cover the entire surface of Earth (open ocean, coastal ocean, forests, grasslands, wetlands, lakes/rivers, deserts, tundra, ice/rock, cropland, and urban). The model also nicely links to several socioeconomic elements of sustainable development, such as the different types of capital (human, built, social, and natural) that form an essential element of the World Bank's approach to sustainable development and measures of sustainable social welfare.

4.11.2.2 Models Concentrating on Economy, Energy, and Climate Relationships

IAMs have been very successful in the field of climate change. A large number of IAMs have been developed, and their results are regularly presented to and discussed with decision-makers. In this way, they have clearly influenced policy-making. Examples of interaction between outcomes of IAMs and decision-makers include use and development of the IMAGE model in dialogue with policy-makers in the Netherlands (Alcamo et al. 1996) or the contribution of IAMs to several chapters of IPCC's Third Assessment Report, in particular with respect to mitigation strategies (Metz et al. 2001). Reasons for this include that the issue of climate change refers to a rather complex web of causes, environmental processes, and impacts (which can only be understood well in an integrated way), that many crucial relationships are well known, and, more recently, that an institutionalized policy process exists. As a result, currently more than 50 IAMs exist that cluster around the relationship of economic development, energy use, and climate change. Some of these also describe related issues such as other atmospheric pollutants and depletion of resources. In some publications, these models are referred to as 3E models: Economy, Energy, and Environment.

A clear difference within this group can be made between basic macroeconomic models, with little technological and climate detail, and models that include a detailed description of the energy sector. The first category includes, among others, rather aggregated meta-models that aim to link both economic causes of climate change and the resulting impacts in order to perform cost-benefit analysis, such as the DICE model (Nordhaus 1994) and the FUND model (e.g., Tol 1997, 2003). Both of these have been applied in a large number of studies. A strong point of these models is that they fully describe the cycle—from economic development to climate change, possible damage from climate change, and its feedback on the economy. However, the detail in describing ecological functions in these models is rather low and abstract. In particular, DICE describes climate change in terms of a limited set of equations for global temperature increase with a couple of damage functions. The FUND model, in time, has become more comprehensive in its description of climate change impacts; now, for instance, it also deals with spread of diseases.

Another group of models includes a more detailed description of the energy and the climate system but, in turn, sometimes lacks a feedback on economic development. This includes most of the models used in the recent IPCC *Special Report on Emission Scenarios* study (ASF, MESSAGE-MACRO, MARIA, MiniCAM, AIM, and IMAGE). (Descriptions and references of these models are provided by Nakićenović and Swart, 2000; see also www.grida.no/climate/ipcc/emission/index.htm.) Other influential IAM models that fall into this category are the ICAM model (Dowlatabadi 1995) and MIT's Integrated Assessment Model (Prinn et al. 1998). The ICAM model emphasizes the role of uncertainty. The MIT model consists of a framework of underlying state-of-the-art disciplinary models and probably represents currently one of the most well developed models in the field.

4.11.2.3 Global Change Models

The models in this group are similar to those just described, in that the emphasis is placed on the relationships between energy and the environment. Reflecting a trend of the past 10 years and taking advantage of new computer tools and satellite data, the developers of these models have widened their scope to include other aspects as well, in particular land cover/land use change and the relationships between land use change and climate change. For this reason, we have chosen to characterize them as global change models. This section focuses on the IMAGE and AIM models.

The IMAGE model is one of the well-known integrated assessment models in this category (IMAGE-team 2001). It includes a description of the energy/industry system, of land use change, and of the climate system, partly based on 19 global regions and partly on a 0.5x0.5 grid. In more recent years, it has both aimed at applications within the climate change community (for example, in the IPCC-SRES) and at much broader applications, such as UNEP's *Global Environment Outlook* (UNEP 2002). Ecological services that are described within the model include the role of ecosystems within carbon and nutrient cycling, provision of food and energy, and some more abstract indicators of ecological functioning. The number of linkages in IMAGE between the environmental system and socioeconomic system, however, are limited. Within its more narrow focus of environmental problems, nevertheless, horizontal integration is exemplary. Vertical integration is more limited, as there is a lack of feedback from the environmental impacts calculated by the model on the macroeconomic trajectories that the model assumes.

AIM is a set of models developed by the National Institute of Environmental Studies in Japan, including a general equilibrium model but also some fuller integrated assessment models (Kainuma et al. 2002). In terms of its coverage and applications it is quite similar to the IMAGE model, although the emphasis is more on East and South Asia.

4.11.3 Conclusions

Over the years several IAMs have provided relevant information on the future of ecological services. This is in particular the case for regulating and providing ecological services such as food and water provision and those related to biogeochemical cycles. Only a few models have been specifically developed to provide information on "sustainable development" issues, however. (That term is used here to indicate the central focus of the MA—ecological functions and their relevance for human well-being.) Existing models only cover trends for a few selected services. Evaluating IAMs against the three criteria described earlier leads to several conclusions.

4.11.3.1 Integration and Feedbacks

Although the integration in most models is high from the perspective of the limited (environmental) problems they were developed for, their integration from a perspective of the MA's objective is still rather low. In particular, the number of feedbacks that are included from ecological changes on socioeconomic drivers are scarce. (Some exceptions are the impacts of food production and climate policy on socioeconomic drivers.)

We believe that a better description of the linkages and feedbacks from an overall sustainable development perspective (instead of a single issue perspective) could improve the relevance of a selected set of IAMs for broad global assessments. An international attempt to further specify these linkages and establish priorities for them against an overall ''sustainability science'' context could be helpful.

At the same time, it is clearly not realistic to expect models to be both comprehensive and detailed. Therefore, nested approaches could provide a significant improvement over existing work. Here, comprehensive but more aggregated models provide drivers for more dedicated (and thus more detailed) models. Such models could focus on particular issues or regions.

4.11.3.2 Level of Geographical Aggregation

The processes in ecosystems and hence the provision of ecosystem services are most adequately considered as nested dynamical processes occurring at various scales (Gunderson et al. 1995). A proper understanding of their response under human-induced direct and indirect (such as climate change) perturbations demands models that cover various scales in both space and time.

Given the purpose of the MA, models needed to acknowledge heterogeneity and include a sufficiently detailed regional/local specificity. With the new tools of geographic information systems and an ever-growing amount of satellite and field data, there is a clear tendency to invest in ever-higher spatial resolution in models. This has a price, too, as it usually implies less than global or even regional coverage. At the same time, given ongoing globalization, many economic processes potentially have ever-wider consequences for ecosystem perturbations. Thus, at the economic level as well, understanding the nature and dynamics of regional differences and interregional links, in particular trade, will be an important research issue for integrated modeling in the coming years. Again, a nested approach to integrated assessment modeling could be a helpful way forward, in which global models provide context for detailed, regional (ecological) models.

4.11.3.3 Areas That Are Poorly Covered

Ideally, IAMs should cover a wide range of different aspects of sustainable development if they are to be used for policy-relevant assessment with as broad a scope as the MA. Clearly, some areas of ecosystem change are poorly covered. In particular, the linkages between ecosystem change and human development, in a broad economic and sociopolitical sense, are weak or absent in most IAMs. The institutional components among them are notoriously weak. This reflects the large and growing complexity of the economic and social processes in an ever more integrated world.

There is as yet limited experience with and agreement on how to connect the various layers of a vertically integrated model. The emerging science of complexity, especially when it entails detailed simulation models of socioecological systems, may indicate a way forward (Janssen 2003; de Vries and Goudsblom 2002). Another strategy is to include qualitative narratives and then try to support certain parts of the narratives with the rigor and consistency of quantitative models. Some parts of the environment are almost systematically lacking in IAMs, such as marine ecosystems and coastal zones. This is also the case for a large number of ecosystem services, in particular regulating and cultural services. Our representation of the parts that are included suffers from an incomplete understanding of the underlying processes.

4.11.3.4 Application of IAMs

A major area of use of IAMs is in developing and analyzing scenarios. Models should be only one tool in this process, their main role being to generate and organize quantitative projections. Descriptive narratives are powerful tools to convey the broader significance of scenarios, as indicated, for instance, in IPCC's SRES scenario work. Among other things, narratives bring in qualitative elements that quantitative models cannot handle and convey that different scenarios constitute very different worlds and, therefore, strategies that will work in one future world may very well be out of place in another.

Finally, we need to note that uncertainties are a key element in IAMs, given their high complexity and focus on decision-making. These uncertainties include, for example, variability of parameters, inaccuracy of model specification, and lack of knowledge with regard to model boundaries. Although the existence of uncertainties has been recognized early in the process of developing IAMs, in many of them uncertainty analysis is included only partially or not at all. Several new projects have been set up to work on uncertainties in a more specific way (see, e.g., www.nusap.net).

4.12 Key Gaps in Our Modeling Abilities

Many of the shortcomings of models pertain to data limitations or limitations of the models themselves. For example, our ability to incorporate spatially explicit data is often lacking. Two fundamental conceptual gaps stand out as especially important.

The first gap concerns the absence of critical feedbacks in many cases. Examples can be found in virtually every arena of forecasts. As food supply changes, so will patterns of land use, which will then feedback on ecosystem services and climate alteration and future food supplies. Land use changes modify the climate, but the climate then alters the vegetation possible on any parcel of land, which in turn constrains the types of land cover possible. These types of feedbacks are lacking throughout. This means the forecasts are best over shorter time scales, before the feedbacks are given time to resonate back through systems. It may be that 50 years, which is the timeframe of the MA projections, is sufficiently short that the absence of critical feedbacks is not as much of a liability as it might seem at first glance. If these feedbacks are important, our models may be seriously wrong in their predictions.

The second major gap is the absence of theories and models that anticipate thresholds, which once passed yield fundamental system changes or even system collapse. We know it is possible to hunt or fish a species to extinction—to total collapse, in other words. A short time frame for forecasts does not confer any immunity to thresholds, since we may be very close to certain thresholds at this point in time. For this reason, the greatest priority for advancing MA models is more explicit attention to anticipation of thresholds.

Finally, there is the issue of model transparency and the use of models by decision-makers. Much of what makes models fail as useful assessment tools is that modelers often get the technical process of modeling right but do not account for the fact that assessment tools need to be part of existing social and political processes. There needs to be much more work aimed at: how to ask modeling questions so that they are relevant to policy and other processes; how to find new ways to communicate complexity to nonspecialists because of the abundance of nonlinearities, feedbacks, and time lags in most global ecosystems; how to elicit knowledge with and from stakeholders at different levels of organization (local, regional, national, international), how to understand the way models fit or do not fit into social and political processes; and how to communicate model uncertainty to non-specialists.

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