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Integrated Assessment Models of the Food, Energy, and Water Nexus: A Review and an Outline of Research Needs

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Abstract

Food, energy, and water (FEW) systems play a fundamental role in determining societal health and economic well-being. However, current and expected changes in climate, population, and land use place these systems under considerable stress. To improve policies that target these challenges, this review highlights the need for integrating biophysical and economic models of the FEW nexus. We discuss advancements in modeling individual components that comprise this system and outline fundamental research needs for these individual areas as well as for model integration. Though great strides have been made in individual and integrated modeling, we nevertheless find a considerable need for improved integration of economic decision-making with biophysical models. We also highlight a need for improved model validation.

INTRODUCTION

Historically, agricultural land, energy, and water have been viewed as inputs for the production of food; however, the ethanol boom and the potential for second generation feedstocks made from perennial crops show that energy can also be a direct output of agriculture. The events of recent decades have also made clear the profound consequences that agriculture can have for the quality and quantity of water available for other uses. We now understand that important feedback loops and trade-offs are omitted when treating food, energy, and water as unidirectionally coupled. Furthermore, new challenges to maintaining sustainable food, energy, and water quality and quantity are on the horizon. For example, projections from climate models suggest that some regions with highly productive agricultural lands will increasingly face weather extremes such as drought and floods, requiring adaptation and mitigation policies at the farm and watershed levels to reduce their impacts. Failure to understand feedback effects between biophysical and economic systems can lead to unintended and undesirable outcomes from these policies.

From October 12–13, 2015, a workshop funded by the US National Science Foundation was held at Iowa State University in Ames, Iowa, with a goal of identifying research needs related to economic and biophysical models coupled within the food, energy, and water (FEW) system.[1] The workshop identified two overarching roles for economics research in coupled systems. First, economists and other social scientists play a critical role in adapting natural and physical science models for use in economic decision-making and policy analysis. This is illustrated in **Figure 1**, which depicts a highly stylized schematic for an integrated assessment model (IAM) of the FEW system. The top level represents human agent behaviors (economic decisions, policies, and institutions) that directly affect a wide range of physical and natural systems. The first level of an IAM is therefore primarily in the social science domain. The second level depicts models for those natural and physical systems. These models fall primarily in the engineering, biological, and physical sciences. The third level returns to the domain of economics and social sciences, as it depicts the use and value of environmental services as they are altered through the system. The diagram highlights the need for an integrated approach that accounts for crucial links between natural systems and human decisions, policies, and values. Although economists have developed extensive research to study the behavior of economic agents and policy makers shown in the top layer, these studies often stop short of linking those decisions to the biophysical models in the middle layer. In turn, detailed biophysical models have been developed for individual components of the natural system, including linkages across some of those models (e.g., crop growth, land use, fisheries, and water quality), but these need to be linked to models of human decision-making and values. As economics provides bookends for the IAM, economists must play a prominent role in research that takes advantage of biophysical models for use in policy evaluation and welfare analysis.

In addition to acting as the essential lens through which the biophysical system is transferred to the human domain, economic decision-making is arguably the major driving factor in environmental and land-use changes. Yet outside of the economics literature, such decision-making is often taken to be random or irrational in linked models, or it is even altogether ignored. Examples include models of ethanol production that assume conversion of land to biofuel crops based only on climate variables, regardless of profitability or proximity to processing facilities;

[1] Approximately 80 people attended the workshop, with about half representing the social sciences (primarily economics), and the rest representing the physical and natural sciences. This focus was chosen so that workshop findings would be particularly relevant to the US National Science Foundation's Social, Behavioral, and Economic Sciences research needs while also including the critical connectivity needed between social sciences and other disciplines.

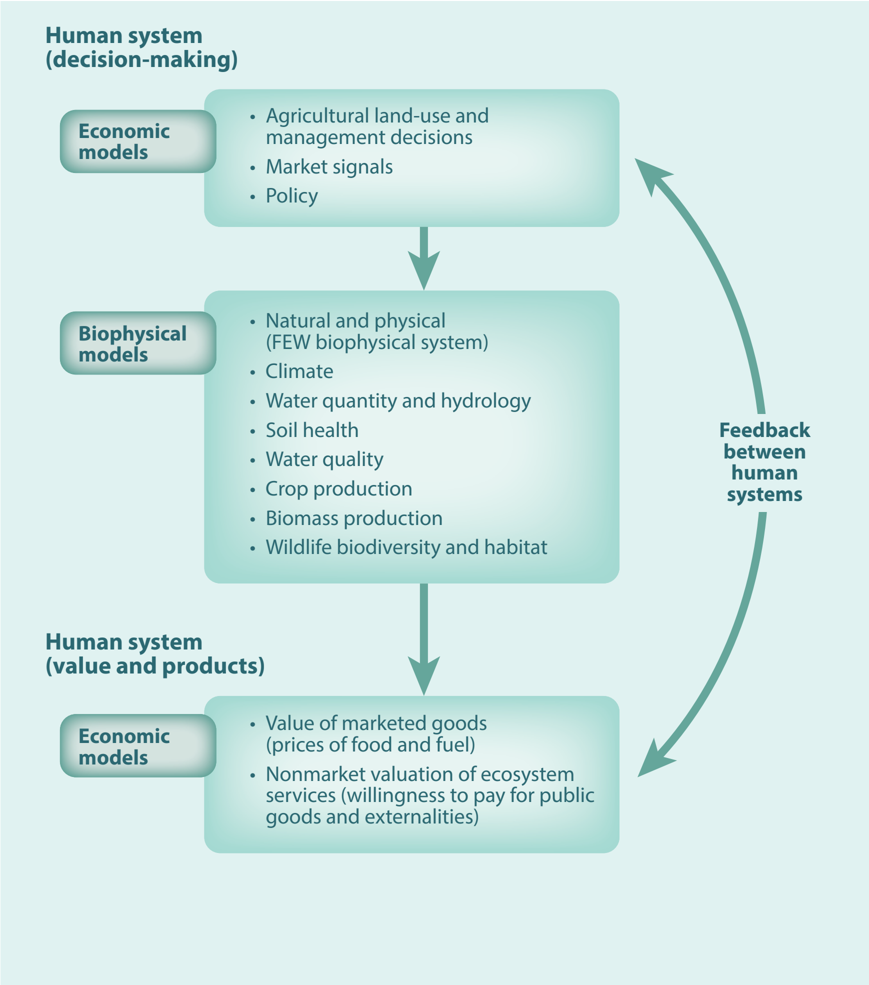

Figure 1

The food, energy, and water (FEW) nexus: a simple schematic of complete integrated assessment models.

models of fishery population dynamics that assume fishing pressure is uniform across the stock and that ignore economics of scale and cost; and models of the impact of land retirement programs on environmental quality that neglect rebound effects in other locations due to price signals. In such cases, omission of the economics component can fundamentally alter the dynamics of the integrated system and lead to poor policy recommendations.

This review summarizes opportunities and challenges for integrated modeling of the FEW system, drawing upon discussions at the workshop as well as prior literature. The first section discusses the motivation for integrated assessment modeling of the FEW nexus rather than considering system components separately. The second section provides an overview of models for components of the FEW system, including improvements needed in those models. The third section describes the advances that will be needed for improved integration of FEW components. We conclude with a summary and suggestions for advancing integrated modeling of the FEW nexus.

THE IMPORTANCE OF DEVELOPING INTEGRATED ASSESSMENT MODELS OF THE FOOD, WATER, AND ENERGY NEXUS

Policies designed to address a single objective can have unintended consequences, often referred to as policy spillovers. Initial evaluations of the Renewable Fuel Standard, for example, focused largely on the energy system and carbon dioxide emissions while ignoring spillover effects into food and water systems and concluded that this program would have favorable environmental impacts (Farrell 2006). However, upon implementation, it became clear that this diversion of corn into the energy system has important impacts on corn prices and production and on the production of other crops through global markets. Searchinger et al. (2008) were among the first to attract wide attention to the market-mediated global impact of US biofuel policies. Ensuing work softened some of these results but not the insight into the need to consider the implications beyond local systems. Although the predicted land-use changes differ widely among modeling systems and approaches (reflecting large uncertainties still remaining), Hertel et al. (2010a) estimate that these market-mediated linkages resulted in conversion of more than four million hectares of pastures and forests to cropland in the rest of the world. As a result, the initial reduction in greenhouse gas (GHG) emissions due to the substitution of bioenergy for fossil fuels was largely offset by the subsequent release of terrestrial carbon. These environmental damages increase further when considering their interplay with water systems. Taheripour et al. (2013) find that, when the expansion of irrigated crops is restricted in regions already experiencing physical water scarcity, terrestrial carbon releases rise by 25%. They attribute this increase to the lower average yields from rain-fed crops: When high-yielding irrigated crop production is curtailed, total cropland area must expand more, and it must expand into more carbon-rich regions. This indirect land-use change effect is an example of the need for a global integrated systems analysis of renewable energy policies within a fully developed FEW system framework (Liu et al. 2015). The diverging results obtained by different modeling groups and systems highlights the need for renewed efforts in this field.

In addition to unintended consequences of individual policies, there can be spillovers across different policies. As an example, a policy that stipulates minimum flow requirements for fish habitat may interact with a policy that allocates surface water for irrigation of farmland. The possibility of policy spillovers motivates the need for an integrated human–natural model of the FEW system. Capturing unintended effects of policies requires understanding human responses to policy as well as to the consequences of those actions for outcomes in the natural system. Spillovers often arise because of effects transmitted through markets. In the example of indirect land-use change, the increase in crop prices provides incentives for conversion of forest and pasture lands. Thus, within the human system model, it is important to represent markets and the linkages among them. A related challenge in properly accounting for policy spillovers is that markets are often global in extent. Agricultural commodities are produced and traded across the globe, which means that policy spillovers can have far-reaching effects. In some cases, a global model may be needed to adequately capture spillovers.

An alternative to policies that pursue a single objective is multicriteria decision-making, representing the effects of policy spillovers on the multitude of ecosystem services generated by the FEW system. These analyses identify cases where there are trade-offs among ecosystem services, such as increased land allocated to crops resulting in less carbon sequestered in forests. There may also be cases where different ecosystem services are complementary, such as policies encouraging the establishment of permanent vegetative cover that provides habitat for grassland birds, reduces soil erosion, and improves water quality. An integrated model of the FEW system can be combined with optimization techniques to estimate efficiency frontiers that characterize the trade-offs or complementarities among different ecosystem services (Rabotyagov et al. 2014).

One core challenge of incorporating all of the relevant component models and their feedbacks is establishing the required level of detail for each component. Models for individual components of the FEW system often incorporate substantial detail on the mechanistic aspects of the component in question, an approach that is often regarded as a structural model. In contrast, a tractable integrated model often requires simplified forms of one or more component models, an approach commonly referred to as a reduced-form model. In the following section, we briefly summarize the core components for an IAM of the FEW system and include comments on differing methodologies and levels of detail.

AN OVERVIEW OF MODELING CAPABILITIES OF THE FOOD, WATER, AND ENERGY SYSTEM COMPONENTS

Crop Modeling

A crop model, in the broadest sense, is a mathematical relationship that can be used to predict crop yield. An example of a reduced-form crop model is a statistical relationship that uses monthly average temperature and rainfall to predict yield. Structural models include more mechanistic detail and predict crop growth, development, and yield based on biophysical principles, genetics, management, climate, and soil characteristics. These structural models often provide information on crop yield, nutrient runoff, and other environmental impacts.

Crop models can serve multiple purposes. In a practical sense, they can be used as decision support tools for predicting expected yields. Such models for various crops can be combined into a unified framework for decision support or other purposes. A well-known example is the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al. 2003), which currently combines biophysically based models for 42 crops along with data management tools for soils, genetics, climate, and other inputs into a freely available system. Another example is the Agricultural Production Systems Simulator (APSIM) (Keating et al. 2003). Similar to DSSAT, APSIM also contains modules to manage input and output data.

Crop models are also used as components of larger modeling systems. Although crop yield may be a secondary interest in such models, including crop yield as a criterion for model calibration can give improved results for other processes (Nair et al. 2011). Modern global climate models also include a dynamic vegetation model in which the evolving climate affects simulated growth of vegetation, whereas the vegetation affects heat and moisture exchange with the atmosphere (Foley et al. 2000).

Many crop models have been developed, including multiple models for individual crops such as wheat and maize. These models are seldom evaluated consistently, making it difficult to compare model performance or to improve models by testing them under a wide range of conditions. These concerns led to development of the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al. 2013). The goal of AgMIP is to improve development of crop modeling to address issues such as the influence of climate change on agricultural production. AgMIP includes economic modeling as an integral component to address issues such as the effect of bioenergy demand on food prices (Lotze-Campen et al. 2014) and the effect of climate change on agricultural land use (Schmitz et al. 2014). One important insight from AgMIP is that model ensembles often perform better than individual models.

In addition to a suite of structural (biophysical) models, there is an emerging literature using reduced-form approaches. These approaches take advantage of extremely detailed panel data sets to study the effects of weather on crop yields. The unit of observation is often a county or field in a particular year. The employed research designs control for unobserved factors at the county or field level that may influence crop yields but remain fixed over time (e.g., soil type, slope of the land). Variation in key weather parameters such as temperature and precipitation within a fixed location over time is then used to identify the effect of changes in weather on crop production (Lobell et al. 2011, Schlenker & Roberts 2009).

Economic Models of Land Use

In their simplest form, economic land-use models explain or predict the purpose of a parcel of land based on its characteristics and economic drivers. Land-use models may also explain other variables, such as output levels, the levels of inputs, and environmental outcomes. A key feature of land-use models used by economists is that they generally assume that land-use decisions are decentralized and based on economic opportunities (i.e., in economic equilibrium, each land unit has been dedicated to the alternative use offering the highest net economic return). Because returns to alternative activities generally depend on factors that vary across land units, an economic equilibrium will generally involve a pattern of multiple land uses across space that depend on exogenous factors, such as prices or climate, that are taken as inputs into the model. The land-use model is then used to infer the change in land use and possibly other variables caused by a change in one or more of these external factors.

Economic land-use models can be structural or reduced form. Other categorizations are possible, for instance, whether models are static or dynamic or whether they are partial or general equilibrium (Khanna & Zilberman 2012). Partial equilibrium models consider a single market typically corresponding to a specific geographical area, whereas general equilibrium models account for multiple interacting markets and may be global in scope. However, some partial equilibrium models can include several markets and be global in scope too. The economic rule determining the allocation of land across activities is generally made explicit within a structural model through a representation of technological possibilities (e.g., production functions) in the context of a computable general equilibrium model such as the Global Trade Analysis Project (Randhir & Hertel 2000), the backward Lagrangian stochastic model (Rosenzweig & Parry 1994), or constrained linear programming representations of production possibilities (Adams et al. 1990, McCarl & Schneider 2001). In contrast, reduced-form approaches do not rely on explicit technology representation and instead directly relate land use to exogenous factors, such as crop returns and local biophysical characteristics (Pautsch et al. 2001, Plantinga et al. 1999, Searchinger et al. 2008, Stavins 1999).

A structural representation allows incorporation of spatially disaggregated information made available from natural science models, notably relationships between biophysical characteristics and management practices, such as fertilization and yields (Mérel & Howitt 2014). However, these models may be poorly identified in an econometric sense (Paris & Howitt 1998) and are typically limited in their ability to capture unobserved, idiosyncratic factors affecting land-use decisions; in addition, adequate microlevel production cost data may not be available. In contrast, reduced-form models have the advantage of implicitly capturing economically relevant factors (Plantinga et al. 1999, Stavins 1999). In addition, because the technology is implicit, it often means that larger data sets can be mobilized to estimate key behavioral parameters (e.g., acreage price elasticities) (Hendricks et al. 2014). A disadvantage is that behavior along the intensive margin has generally been more difficult to observe than land use per se, which limits the types of inference that can be made from such models.

Structural and reduced-form approaches are not mutually exclusive. An approach known as positive mathematical programming seeks to combine the advantages of a detailed representation of technology with information obtained from observed economic behavior, notably actual land use, through a nonlinear programming approach (for a recent review, see Mérel & Howitt 2014).

Water Quality Models

Dozens of water quality models have been developed to assess the transport of one or more pollutants over various landscapes, in stream systems, and at a specific scale or a range of scales (e.g., Borah et al. 2006, Bouraoui & Grizzetti 2014, Daniel et al. 2011, de Brauwere et al. 2014, Gao & Li 2014). Many of these models can be described as structural models (i.e., process oriented or mechanistic in nature), such as the Soil and Water Assessment Tool (SWAT) ecohydrological watershed/river basin–scale model (Arnold & Fohrer 2005; Arnold et al. 1998, 2012; Gassman et al. 2007; Williams et al. 2008). Other types of models are also used for simulating pollutant transport in watersheds or river basins, including artificial neural networks (e.g., Gazzaz et al. 2012, Jiang et al. 2013) and statistical approaches, such as the Spatially Referenced Regressions on Watershed attributes (SPARROW) model (LaBeau et al. 2014, McLellan et al. 2015, Preston et al. 2011, Schwarz et al. 2011, Smith et al. 1997). Finally, economists have also used reduced-form approaches to directly relate water quality to policy or economic drivers of interest.

The aforementioned SWAT model is a widely used structural model. It is a conceptual, long-term, continuous, watershed/river basin–scale simulation model that operates on a daily or sub-daily time step. Key components include precipitation and other climatic inputs, hydrology, plant growth, management practices, erosion and sediment transport, nutrient transport and transformation, and pesticide transport.[2] SWAT has been successfully used across a wide range of watershed scales (ranging from <1 km^2 to entire continents), environmental conditions, and types of applications, as documented in review studies (Arnold & Fohrer 2005; Bressiani et al. 2015; Douglas-Mankin et al. 2010; Gassman & Wang 2015; Gassman et al. 2007, 2014; Krysanova & Arnold 2008; Krysanova & White 2015; Tuppad et al. 2011).

Reduced-form approaches use a statistical model that relates data on water quality outcomes to data on important biophysical and socioeconomic determinants of water quality. This provides an alternative to mechanistic, biophysical-based models by identifying a few key parameters and implicitly controlling for many of the biophysical processes that underlie structural models. The outcome of interest is often a measure of water pollution effluent, either from a point source (e.g., an industrial facility that discharges directly into waterways) or a nonpoint source (e.g., runoff from an agricultural field). These studies often develop a theoretical economic model of municipal or industrial behavior that determines emissions and then studies how government interventions, effluent limits, or regulatory frameworks may influence emission levels (Cohen & Keiser 2015; Earnhart 2004a,b; Shimshack & Ward 2008). Monthly plant-level panel data on effluent allow researchers to leverage research designs that separate the effects of policy changes from other determinants of emissions that may remain fixed over time, such as higher polluting industries or incomes of surrounding populations. Other studies directly examine the effects of policies on ambient measures of water quality. Examples include analyzing the effectiveness of the Conservation Reserve Program (Sprague & Gronberg 2012), the US Clean Water Act (Keiser & Shapiro 2016, Smith & Wolloh 2012), fracking activities (Olmstead et al. 2013), transboundary pollution (Lipscomb & Mobarak 2014; Sigman 2002, 2005), and other water pollution regulations abroad (Greenstone & Hanna 2014). These efforts have been much more limited due to the lack of high-quality ambient measurements that track changes in water quality over time.

An example of a model that combines both reduced-form and structural approaches is SPARROW. This model uses a statistical approach to relate in-stream levels of pollutant loads to both upstream point sources and nonpoint agricultural and urban sources for watersheds ranging

[2] Extensive documentation of SWAT versions, supporting software and other SWAT-related resources can be accessed at **http://swat.tamu.edu/**.

in size from tens of square kilometers to entire river basin systems that drain large portions of continents (Preston et al. 2009, Smith et al. 1997). This statistical approach is constrained by mechanistic components that model fundamental hydrological aspects of the study system (e.g., flow paths, transport processes, mass–balance constraints). SPARROW is typically used to estimate water quality levels in streams, especially for large river systems in the United States. It has also been used to explore scenarios such as potential water quality impacts in the Great Lakes region due to future land-use change (LaBeau et al. 2014) and reduction of in-stream pollutant levels due to the implementation of widespread best management practices (BMPs) across the Corn Belt region (parts of the midwestern United States) (McLellan et al. 2015).[3]

It is worth noting that the FEW nexus also incorporates water storage issues as well as ground water. As one reviewer of this article noted, water management is a dynamic process related to snow and ice melt. Xie & Zilberman (2016) provide an excellent overview of work linking water storage to conservation concerns. Howitt et al. (2014) consider surface water and groundwater exchange in a model related to California drought and its consequences.

Bioenergy Models

The emergence of bioenergy as a competing source of demand for land and water has linked agricultural and energy markets, creating a need for improved modeling of agricultural markets that recognize joint dependence on scarce land and water resources. Numerous models have been developed to analyze the implications of changes in bioenergy demands for land use, food and fuel prices, water consumption and quality, and climate change mitigation (Khanna & Zilberman 2012, Khanna et al. 2014). These assessments are increasingly based on models that capture economic behavior and incorporate crop production technologies, biophysical and biogeochemical factors that affect crop productivity and soil organic matter, hydrological effects on water and water quality, and land suitability and availability constraints (Chen et al. 2014, Housh et al. 2015).

Models of food and water systems that include energy, not only as an input for production but also as an output in the form of renewable energy, show the importance of distinguishing among different types of renewable fuels (Hudiburg et al. 2016). An alternative to grain- or sugar-based ethanol or vegetable-based biodiesel is cellulosic biofuels from dedicated energy crops. These can often be grown on low-quality land and may enhance soil organic matter and reduce runoff. Cellulosic biofuels thus have the potential to meet demands for renewable energy with fewer adverse impacts on food/feed production than food-crop–based biofuels such as grain ethanol. Representation of these models within crop growth and water quality models, however, is seriously underdeveloped. With numerous choices among energy crops and considerable spatial heterogeneity in the economic and environmental impacts of using them for biofuels, integrating spatially resolved economic and biophysical modeling in FEW systems models is critical to understanding trade-offs and complementarities. Additionally, cellulosic biofuel feedstocks impact the environment in multiple ways, including affecting GHG emissions, water quality, and biodiversity. These effects differ across feedstocks and can be positive or negative. Again, these effects are incompletely represented in existing crop and water quality models. System-of-system models are now being developed to incorporate these multidimensional effects of food and energy production (Housh et al. 2014).

[3]Additional resources regarding documentation or applications of SPARROW can be accessed at **http://water.usgs.gov/nawqa/sparrow/**.

RESEARCH NEEDS RELATED TO COMPONENTS OF INTEGRATED ASSESSMENT MODELS

Improving the usefulness of individual modeling components of the FEW system as part of IAMs presents a number of challenges and research opportunities. First, there is a need for increased modeling capacity to represent a wider range of land-use options and their resulting biophysical processes, including their effect on ecosystem services of relevance at the human scale. An example of the need for further model refinement was noted in the workshop discussion related to modeling of bioenergy crops such as cellulosic biofuel feedstocks. Incorporating information from field studies will be necessary to accurately parameterize and calibrate models to represent these crops. Other examples include the need for land-use, crop, and water quality models that appropriately represent (*a*) the movement of nutrients and water through tile drains in agricultural landscapes, (*b*) in-stream sediment and nutrient processes in rivers and streams, (*c*) the adequate representation of wetlands in water quality models, and (*d*) the impacts of conservation practices on crop yields (Rabotyagov et al. 2014), among others.

Existing models tend to individually examine strategies to address environmental problems. However, FEW systems often generate multiple environmental impacts, some of which occur as complements, such that addressing one leads to cobenefits by reducing others. For example, changes in cropping systems can affect carbon sequestration, wildlife habitat, and water quality. Developing models that incorporate these multiple impacts can lead to more holistic approaches to addressing multiple externalities simultaneously and designing policies to achieve sustainable FEW systems (Housh et al. 2015).

A second area where improvement is needed is the better incorporation of adaptation options and behavior in individual model components. For example, economic models of the FEW system need significant improvement in their ability to represent adaptation of economic agents in response to climate change and other events. One strategy is to adopt reduced-form approaches (Schlenker et al. 2005, 2006), which, under strong information assumptions, can be said to incorporate adaptation. These methods do not describe the specific process by which adaptation will occur, such that when new technologies are possible, these methods are unlikely to be reliable. Furthermore, understanding how adaptation will occur and what technologies will be adopted is often critical for understanding the question under study.

One potential approach for improved structural modeling of adaptation is to combine stated and revealed preference information (Freeman et al. 2014, Kling et al. 2012). In simple terms, this involves combining information on what actors say they will do (stated preferences) with knowledge of what they actually do (revealed preferences). This literature has identified conditions under which it is possible to combine information from observed behavior that can be used to infer revealed preferences with survey-based findings that provide stated preference information. By combining these two sources of information, the analyst can combine information about out-of-sample behavior, such as the adoption of new technology in response to climate change, with observed behavior where actions are known to be constrained by budget limitations and price signals. Other approaches to better represent adaptation are also needed.

A third area in need of model improvements is especially relevant to the economic decision-making underlying land-use models, which typically assume rational and often static economic behavior. These modeling assumptions are convenient—rationality allows the market outcome to be replicated by an optimization program akin to a central planner's optimization decision, and static behavior is useful because it is often computationally infeasible to solve for a dynamic market equilibrium. However, there are situations in which these assumptions are too limiting to accurately reflect underlying behavior. Agent-based modeling provides a potential approach to represent this behavior in a simulation-based modeling environment (Farmer & Foley 2009). Ng et al. (2011) developed an agent-based model of the crop and BMP decisions of farmers, which was then linked with a SWAT model of a watershed.

Zhao (2015) developed an irrigation technology adoption model that relaxes these assumptions by allowing farmers to decide dynamically and suboptimally when to adopt a new irrigation technology. Decisions are made both in response to existing information and in anticipation of future new information about the technology from experts and other adopters (i.e., their neighbors), but learning can be non-Bayesian, and decisions can be subject to behavioral distortions. Previous research has found that noneconomic motivations, such as environmental stewardship and family succession, are significant drivers of land management decisions. For example, higher perceived efficacy of a conservation practice among farmers in the western Lake Erie Basin is strongly linked with adoption of filter strips and timing-related phosphorus practices (Howard & Roe 2013, Wilson et al. 2014). Accounting for such nonoptimizing behavior approaches that augment traditional dynamic optimization models is an important research need.

Finally, there is a need to incorporate national and international market responses into regional analyses. It is often natural to study the FEW system at the level of a local or regional watershed, as this is the level at which land, water, energy, and food production is most immediately observable. However, food and energy markets are increasingly globalized, and there is growing recognition that water use is strongly influenced by global trade (Dalin et al. 2012, Hoekstra & Mekonnen 2012, Konar et al. 2013). An example of the importance of trade arises in assessment of the Renewable Fuel Standard, where international market responses played a critical role in the final consequences of policy (Elobeid et al. 2013, Fabiosa et al. 2010, Hayes et al. 2009, Hertel et al. 2010b, Taheripour et al. 2013). Climate change reinforces the imperative for incorporating trade into the analysis, as climate is a key determinant of comparative advantage, and comparative advantage shapes international trade. Thus, if climate alters a region's comparative advantage, it will also alter trade patterns, thereby having an effect on the local demand for services from the FEW system. This can give rise to unexpected results (see, for example, Hertel et al. 2010a). Another good example of modeling that incorporates trade effects is the report by Laborde (2011), which uses computable general equilibrium methods to evaluate the land-use and emissions effects of European biofuel policies.

One approach for considering multiple levels of spatial detail is nested modeling. The feasible level of resolution diminishes at broader scales, but with thoughtful nesting of models, it is possible to include both sufficient local detail as well as spillover and interaction effects. Early approaches to this problem are offered by Britz & Hertel (2011) and Pelikan et al. (2015). In short, there is a significant need for models that capture key national and international market responses to FEW system changes that are tractable and can be easily integrated with regional and local FEW modeling systems.

RESEARCH NEEDS RELATED TO MODEL INTEGRATION

There are a number of research challenges in developing IAMS for the FEW system that are not specific to individual component models but arise when these models are brought together. Some of the issues are conceptually straightforward but are serious impediments in practice, and other issues require conceptual innovation as well. We discuss a number of these issues below.

Tractability Versus Realism

A fundamental challenge in the development of IAMs is the trade-off between model tractability and the level of detail with which the economic behavior, crop growth, and watershed processes are modeled. As noted above, economic models that incorporate dynamic behavior should be further developed, but these models need also to be tractable for integration. Goetz & Zilberman (2000) provide a stylized dynamic economic model of phosphorus management that retains model tractability by simplifying the environmental dimension (see also Iho 2010; Iho & Laukkanen 2012; Xabadia et al. 2006, 2008). Their model permits analytical tractability but ignores realistic features of agricultural landscapes and hydrological processes that imply more complicated nutrient dynamics in soils (Knapp & Schwabe 2008, Segarra et al. 1989) and in receiving water bodies (Carpenter et al. 1999).

On the other hand, most current state-of-the-art models of environmental processes are simulation-based approaches with a high level of detail. For example, surface hydrology models, such as SWAT, simulate stream flows as a function of many spatially heterogeneous factors, such as land use and land cover, soil type, slope, and climate (Jayakrishnan et al. 2005). Given the complexity of dynamics in such detailed hydrological process models, integrated models that use detailed biophysical representations often simplify their economic models. Farmers are typically assumed to have myopic expectations and to make current cropping and land management decisions based on current, and possibly past, conditions. For example, simulations based on a SWAT model of Lake Erie (Bosch et al. 2013) assumes the amount and location of conservation practice adoption and ignores individual farmers' responses to policies and the resulting adoption decisions at the landscape scale.

The degree to which all parts of an IAM need to be highly realistic depends on the research question. IAMs are often used to project future scenarios of economic and environmental outcomes based on baseline and alternative conditions, including policies. In such applications, realism in modeling farmer behavior and environmental dynamics is important, and a more realistic model of farmer decision-making is warranted. On the contrary, if the goal is to identify the optimal resource management solution, then solving for the intertemporal optimal allocation of agricultural production and resource use requires model tractability. In this case, much of the agent and spatial heterogeneity is simplified, so that a tractable, stylized representation of the natural resource dynamics is achieved. Although such models are still in their infancy, dynamic renewable resource models provide a useful illustration of this approach (Gopalakrishnan et al. 2011, Landry & Hindsley 2011, Ranson & Stavins 2015). The right trade-off between model tractability and realism will depend on the research goals.

CONSISTENCY OF MODEL INPUT DATA AND OUTPUT COMPONENTS

It is widely understood that knowledge gaps on the FEW nexus can only be filled via multidisciplinary research. This requires the development and integration of hydrological, agronomic, economic, ecological, and other models. Importantly, the component models need to operate at similar spatial and temporal scales—both for consistent policy inference and to enable linking, whereby outputs from one model are used as inputs in the next.

Quantitative analysis of the FEW system requires that the underlying data describing the biophysical and economic systems be internally consistent. However, agencies responsible for gathering data on food, energy, and hydrology are separate in most states and countries, and the data are generally inconsistent along various spatial, temporal, and conceptual dimensions. The problem is further complicated by the need for considerable geospatial detail to deal with the challenges facing the FEW system, which typically are highly localized. Moreover, some important research questions are necessarily global in nature, exacerbating these issues. There are currently no consistent global, temporally varying peer-reviewed databases available for analysis of the FEW system. This poses a significant challenge to advancing the science in a variety of critical areas, such as global carbon modeling, environmental impacts of biofuels, and the impacts of climate change on agricultural productivity, among others (Hertel et al. 2010b).

In general, the problem of data reconciliation for FEW systems can be viewed as constructing consistent data from a diverse array of administrative units, such as counties, states, and nations. Most of the gridded data currently used in FEW system analyses are not directly observed but are outputs from data models involving interpolation, extrapolation, matching, and downscaling methods for data reported at the county or state level. Because the assumptions feeding into these different data models are often inconsistent (e.g., political boundaries, seasonality, cropping intensity), the gridded data available for FEW systems analysis are also inconsistent, and researchers often must perform additional ad hoc adjustments. Centralized repositories of data and open source software, such as GEOSHARE, can address some of these problems by allowing these transformations to be easily reused and improved (Hertel & Villoria 2014).

Additional data collection is highly important as well, which typically involves surveying landowners (recent examples include Fleming et al. 2015 and Gonzalez-Ramirez et al. 2015). However, these surveys can be affected by the same issues as any other data set. Unless these surveys are specifically designed for integration with natural science models, important information is likely to be missing. To maximize the value of these data sets, interdisciplinary planning is needed at the survey design stage.

Though the need for spatial and temporal compatibility across models is appreciated, there is little consensus on the best practice for linking inputs and outputs in conceptually credible ways. The nonmarket value of water quality provides an example of this challenge. Land-use models can be linked to hydrological models to produce estimates of average water quality at specific points in space and a given time of the year. These estimates are expressed in terms of physical variables, such as milligrams per liter of total phosphorus. Predicted changes in such measures then must be valued via a linked economic model. In the most general sense, however, the welfare effects of changes in water quality arise from the impact on ecosystem services rather than through the monitored parameter directly. Thus, a means of translating a change in, for example, total phosphorus to a change in a service flow entering a person's utility function is needed. For example, if the value-generating medium is water recreation, then the change in water quality needs to be translated into an impact on the water body that matters for recreation quality or quantity.

Most integrated modeling efforts address these challenges case by case in the context of the specific problem at hand. However, many of the linking needs in the FEW nexus are general, and systematic research that aims to establish best-practice protocols for linking common modeling inputs and outputs would be of value to the broader scientific community. Of highest value would be insights on how to move from physical predictions of changes in convenient indicators, to changes in ecological functions, and finally to changes in services of value to humans.

Differences in Reduced-Form and Structural Models

Different modeling approaches tend to use different types of data. Structural models tend to use detailed scientific knowledge to represent a system's underlying relationships. The data used to parameterize and develop these models can come from a variety of different data sources, some of which may be informative about only a small part of the system and often incorporate data from several experiments.

Reduced-form models, on the other hand, typically capture statistical regularities in the system under study. Such models do not only reflect correlations—many use statistical techniques that are designed to capture causal relationships in the data. These models are, however, typically estimated on data collected from the system of interest, or a system similar to that of interest, and report the statistical precision associated with their estimates. This task is much more difficult for some structural models that incorporate several different data sources and may require expert knowledge to tune the model to give optimal performance.

Both of these approaches are popular and have their own strengths and weaknesses, some of which have been discussed elsewhere in this review. However, building an integrated model from a combination of structural and reduced-form models presents its own challenges. The most widely used structural models are unlikely to represent estimation uncertainty as accurately as popular reduced-form models. Indeed, many of the structural models for individual components do not involve any statistical or econometric estimation. Conversely, the reduced-form models typically will not have as rich an internal structure as the structural models. An integrated model that uses both structural and reduced-form component models may be unsatisfying in both dimensions, having both a simplistic internal structure and unverifiable statistical properties.

There are several ways to address this problem. The obvious approach is to improve the statistical properties of structural models and to add to the internal structure of the reduced-form models through additional disciplinary research. Many of the individual models discussed earlier are essentially deterministic but are used to study stochastic systems. Determining which aspects of those systems are fundamentally unpredictable and modeling them as such would be a valuable scientific contribution that would greatly facilitate integrating those aspects with the rest of the FEW system. There are many cases, however, in which this approach is effectively impossible given the current state of knowledge: Models of climate change are one especially important example.

An interdisciplinary alternative is to develop methods for embedding an existing structural model into a larger statistical structure ex post, rather than ex ante. This could potentially be achieved through statistical and econometric techniques developed for misspecified models. Rudik (2016), for example, uses Hansen & Sargent's (2007, 2008, 2014) robust control framework to add uncertainty over specific modeling assumptions in the dynamic integrated climate–economy (DICE) model (Nordhaus 2008, Nordhaus & Boyer 2000). The robust control approach has been developed for macroeconomic applications; additional research is likely necessary before it or alternative strategies would be widely applicable in other contexts.[4]

In the same vein, methods can be explored to incorporate richer internal structure into reduced-form econometric models. Again, techniques developed in macroeconomics can provide a useful starting point. For example, vector autoregressions are multivariate time-series models widely used in macroeconomics to estimate intertemporal dynamics (Sims 1980). On their own, these models are entirely atheoretical. However, economic theory can often constrain or partially constrain the model's dynamics, and then those dynamics can be given a structural interpretation and used for policy analysis (Kilian 2013 provides a recent review of this literature). In many cases, the causal structure of interest is not completely identified, but a range of plausible dynamics can be identified that is consistent with the empirical data, and the model is said to be partially identified (Manski 1990, 1995; Uhlig 2005).

[4]It should be made clear that these ex post approaches are in many ways inferior to incorporating meaningful statistical uncertainty directly into the structural models and reporting that uncertainty as a model output. For an ex post uncertainty measure to be valid, it will have to make conservative assumptions on the underlying structure and report the results under the worst-case assumptions. Moreover, these methods add an additional computational burden to an already computationally demanding research approach. Both ex post and ex ante methods for incorporating statistical uncertainty should be encouraged, as well as strategies to mitigate the conservativeness and computational burden of these methods.

Evaluation of Integrated Assessment Models

A similar tension arises from differential methods across fields for evaluating, selecting, and aggregating models. Out-of-sample evaluation methods, where models are scored based on their accuracy in making predictions on a new data set, seem especially promising. A focus on out-of-sample prediction accuracy is likely to have positive spillovers regarding some of the challenges already discussed. Because forecast accuracy can only be evaluated by comparing a model's output to real-world data, it implicitly encourages competing models to produce output in the same units and at the same scale and frequency, which in turn makes it easier for the other FEW models to standardize on a common set of inputs.[5] Moreover, by focusing on out-of-sample accuracy, researchers are explicitly aiming to improve the aspect of their models that matters for economic decision-making (Elliott & Timmermann 2008). Finally, out-of-sample tests of forecast encompassing or misspecification (Harvey et al. 1998) can identify areas in which the models can be improved, instead of simply testing whether they outperform a threshold.

Existing out-of-sample evaluation methods in econometrics are able to handle only a subset of the models used in this area. These are models that already produce measures of statistical uncertainty. Out-of-sample analyses do not necessarily resolve any of the issues raised in the previous subsection (Diebold & Mariano 1995, West 1996). In addition, there are technical constraints that can make direct comparison of models awkward (see Clark & McCracken 2013 for an overview of this literature).

Moreover, modelers and policy makers should recognize that even the best models, both IAMs and individual component models, can make large prediction errors. These errors can occur because the system is affected by factors that are not included in the model or because the model misspecifies the way that the variables interact. It is important that the models recognize the potential for such errors by reporting not just the best guess at an outcome but also a range of potential values. Policy making in the FEW system will be more effective if policy makers understand the range of potential outcomes rather than just the expected outcome. Component models that can produce a probability distribution over potential outcomes are much easier to incorporate into economic models of decision-making. In forecasting parlance, this means that interval forecasts or density forecasts are more valuable products than point forecasts.[6]

Finally, it is not clear that choosing the "best" model for an individual system is the right approach. Research in many different contexts has shown that, when multiple models are available for the same system, ensemble or aggregate models usually forecast more accurately than even the best individual model. These findings date back to Bates & Granger (1969) in economics (Timmermann 2006 and Elliott & Timmermann 2008 provide recent reviews, but this is a very active area of research), and recent research has shown that similar results hold in crop modeling and climate change modeling. One of the most important findings from climate model intercomparison projects is that no single best model exists for such a complex coupled nonlinear system (e.g., Gleckler et al. 2008, Mearns et al. 2012). Instead, model intercomparisons are used to explore ranges of uncertainty and the relative likelihood of different possible outcomes. All of the challenges discussed so far are likely to be amplified when trying to aggregate multiple models of the same individual system, but this approach has the potential to extract more accuracy and richer structure from the set of models that already exists.

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[5] The implicit danger is that models may focus on predicting variables that are easy to observe, whether or not those variables are fundamentally important.

[6] Density forecasts can be evaluated out-of-sample as well. See Corradi & Swanson (2006) and Gneiting & Katzfuss (2014) for recent reviews and Rossi (2014) for a recent overview of the policy implications of density forecasts.

Reduced-Form Studies to Evaluate Integrated Assessment Models

The out-of-sample analyses discussed in the previous section are often performed with an eye toward how well IAMs will predict the effects of policy ex ante. However, a fruitful area of research is to also use past events to test the models' predictions ex post. IAMs allow researchers to model complicated economic and environmental systems to better understand the full effects of certain policies. However, this structural approach relies on a number of strong assumptions that govern the spatial and temporal interactions of these systems. For example, an IAM may be helpful to understand how federal conservation programs affect water quality and the resulting economic benefits of these changes. To make predictions of the impact of such policy, an IAM would need to translate funding support of a conservation program into changes in local land use. A hydrologic model would then model how changes in land use affect water quality. A final component of the IAM would predict how changes in water quality affect economic welfare through changes in economic uses, such as water-based recreation, housing, and drinking water.

Each step in this model relies on assumptions governing these responses. Reduced-form methods that rely on natural or quasi-experiments offer a way to test the predictions of the integrated models but without maintaining the assumptions governing each component. For example, ex post studies on policies such as the US Conservation Reserve Program (CRP) to validate one or many steps in the IAM can be performed. Panel data on the location and timing of CRP adoption in combination with data on water quality measurements could be used to estimate the relationship between changes in both CRP acreage and water quality. The analysis would compare findings of this quasi-experimental approach with predictions from the biophysical-based hydrologic model.

The advantage of a reduced-form approach is that it relies much less heavily on theoretical assumptions (e.g., functional form of utility functions, biophysical processes) that may play a critical role in an IAM's predictions. Instead, reduced-form approaches use statistical research designs that take advantage of variation induced by natural or quasi-experiments to identify the effect of a policy or economic change on an outcome of interest (see Imbens & Wooldridge 2009 for a recent survey of these methods). It is important to note that these methods themselves rely on their own set of assumptions (e.g., identifying arguably valid counterfactual units of observation). Nonetheless, by testing the prediction of IAMs versus reduced-form models, one could identify which components of IAMs are understood with greater or less certainty and the impact of this uncertainty on model predictions.

FINAL COMMENTS

Using simulation models for the prospective analysis of FEW systems requires integrating models that describe disparate components of the system. These models are often developed for modeling individual features of the natural system and ensuring system-wide consistency in underlying system boundaries. Assumptions about scale of analysis across these diverse models are critical for meaningful model integration. Economists are particularly well positioned to contribute to these integration efforts because of the importance of accounting for human behavior when modeling the FEW system and because of the importance of statistically sound empirical research methods.

Deliberate human activity has been the dominant factor driving environmental and land-use changes for hundreds of years. Although economists have made great strides in modeling and understanding these choices, the coupled-systems modeling literature has not fully reflected these contributions, and additional economics work is needed. Economic models that assume rationality are widely used in integrated modeling when economists are part of the research team, but many opportunities remain for better inclusion of economic models within the broader modeling community. Moreover, the current generation of IAMs that includes rational agents has emphasized partial equilibrium studies appropriate for smaller systems. The potential for (and consequences of) general equilibrium effects should be studied as well.

It is also important to address potential limitations within models of economic decision-making. Valuable improvements could be gained from developing coupled models that draw insights from behavioral economics. There is increasing evidence that decision-makers deviate systematically from actions that would be predicted by strict rationality, but very few IAMs incorporate this behavior, potentially leading to inaccurate predictions about the effects of policies and regulations. Models of human adaptation and induced technological change are also lacking in many coupled models. Economic models that address dynamic decision-making and uncertainty in decision-making are also underutilized in coupled models of the FEW system.

Second, there is little clarity on how models should be evaluated and compared, both within individual disciplines and as components of larger IAMs. This challenge makes larger integrated modeling exercises extremely difficult. Some potential ways to advance are by developing statistical criteria that measure model performance along the dimensions suitable for inclusion in an IAM as well as infrastructure and procedures to facilitate model comparisons. Focusing on models' out-of-sample distributional forecasting performances, as well as the performance of the IAM overall, is especially promising and of particular importance.

Applications of IAMs tend to estimate the effect of hypothetical future policy actions, but very few studies have used these models to estimate the effect of past policy actions. They offer a well-understood test bed for the IAMs and also contribute to fundamental scientific knowledge through better understanding of the episode in question. The retrospective nature of this form of analysis also presents the opportunity to combine reduced-form estimation strategies with the IAMs as an additional method of validation.

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