

# Research Needs and Challenges in the FEW System: Coupling Economic Models with Agronomic, Hydrologic, and Bioenergy Models for Sustainable Food, Energy, and Water Systems

Catherine L. Kling<sup>1</sup>, Raymond W. Arritt,<sup>1</sup> Gray Calhoun,<sup>1</sup> David A. Keiser,<sup>1</sup>  
John M. Antle,<sup>2</sup> Jeffery G. Arnold,<sup>3</sup> Miguel Carriquiry,<sup>4</sup> Indrajeet Chaubey,<sup>5</sup>  
Peter Christensen,<sup>6</sup> Baskar Ganapathysubramanian,<sup>1</sup> Philip Gassman,<sup>1</sup>  
William Gutowski,<sup>1</sup> Thomas W. Hertel,<sup>5</sup> Gerrit Hoogenboom,<sup>7</sup> Elena Irwin,<sup>8</sup>  
Madhu Khanna,<sup>9</sup> Pierre Mérel,<sup>10</sup> Daniel J. Phaneuf,<sup>11</sup> Andrew Plantinga,<sup>12</sup>  
Stephen Polasky,<sup>13</sup> Paul Preckel,<sup>5</sup> Sergey Rabotyagov,<sup>14</sup> Ivan Rudik,<sup>1</sup>  
Silvia Secchi,<sup>15</sup> Aaron Smith,<sup>10</sup> Andrew Vanloocke,<sup>1</sup> Calvin Wolter,<sup>16</sup>  
Jinhua Zhao,<sup>17</sup> and Wendong Zhang,<sup>1</sup>

**Working Paper 16-WP 563**

March 2016

**Center for Agricultural and Rural Development  
Iowa State University  
Ames, Iowa 50011-1070  
[www.card.iastate.edu](http://www.card.iastate.edu)**

*Catherine L. Kling is Distinguished Professor of Economics, and director of the Center for Agricultural and Rural Development at Iowa State University, Ames, IA. E-mail: [cling@iastate.edu](mailto:cling@iastate.edu).*

This publication is available online on the CARD website: [www.card.iastate.edu](http://www.card.iastate.edu). Permission is granted to reproduce this information with appropriate attribution to the author and the Center for Agricultural and Rural Development, Iowa State University, Ames, Iowa 50011-1070.

The authors and the workshop benefited enormously from the contributions of Maria Jimena Gonzalez-Ramirez, Hocheol Jeon, Yongjie Ji, Fangge Liu, Kevin Meyer, Xianjun Qiu, Adriana Valcu, and Jennifer West. Excellent support from Curtis Balmer, Nathan Cook, Karen Kovarik, Michael Long, Becky Olson, and Deb Thornburg is also much appreciated.

This research was funded in part by NSF grant SES-1541790.

For questions or comments about the contents of this paper, please contact Catherine L. Kling, [cling@iastate.edu](mailto:cling@iastate.edu).

<sup>1</sup>Iowa State University; <sup>2</sup>Oregon State University; <sup>3</sup>Agricultural Research Service, USDA; <sup>4</sup>University of the Republic, Uruguay; <sup>5</sup>Purdue University; <sup>6</sup>University of Illinois and Yale University; <sup>7</sup>Washington State University; <sup>8</sup>Ohio State University; <sup>9</sup>University of Illinois; <sup>10</sup>University of California, Davis; <sup>11</sup>University of Wisconsin, Madison; <sup>12</sup>University of California, Santa Barbara; <sup>13</sup>University of Minnesota; <sup>14</sup>University of Washington; <sup>15</sup>Southern Illinois University; <sup>16</sup>Iowa Department of Natural Resources; <sup>17</sup>Michigan State University

Iowa State University does not discriminate on the basis of race, color, age, ethnicity, religion, national origin, pregnancy, sexual orientation, gender identity, genetic information, sex, marital status, disability, or status as a U.S. veteran. Inquiries can be directed to the Interim Assistant Director of Equal Opportunity and Compliance, 3280 Beardshear Hall, (515) 294-7612.

# Research needs and challenges in the FEW system: Coupling economic models with agronomic, hydrologic, and bioenergy models for sustainable food, energy, and water systems

---

March 2016

Catherine L. Kling, Raymond W. Arritt, Gray Calhoun, David A. Keiser, John M Antle, Jeffery Arnold, Miguel Carriquiry, Indrajeet Chaubey, Peter Christensen, Baskar Ganapathysubramanian, Philip Gassman, William Gutowski, Thomas W. Hertel, Gerrit Hoogenboom, Elena Irwin, Madhu Khanna, Pierre Mérel, Dan Phaneuf, Andrew Plantinga, Paul Preckel, Stephen Polasky, Sergey Rabotyagov, Ivan Rudik, Silvia Secchi, Aaron Smith, Andrew Vanloocke, Calvin Wolter, Jinhua Zhao, and Wendong Zhang.<sup>1</sup>

A white paper prepared for the National Science Foundation's Food, Energy, and Water Workshop held at Iowa State University, October 11–12, 2015.

---

<sup>1</sup> The authors and the workshop benefited enormously from the contributions of Maria Jimena Gonzalez-Ramirez, Hocheol Jeon, Yongjie Ji, Fangge Liu, Kevin Meyer, Xianjun Qiu, Adriana Valcu, and Jennifer West. Excellent support from Curtis Balmer, Nathan Cook, Karen Kovarik, Michael Long, Becky Olson, and Deb Thornburg is also much appreciated.

## 1 Introduction

Agricultural land, energy, and water historically have been viewed as inputs for 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 quality and quantity of water available for other uses. We now understand that there are important feedback loops and trade-offs that 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 extremes such as drought and floods, requiring adaptation and mitigation policies at the farm and watershed level to reduce their impacts. Failure to understand feedback effects between biophysical and economic systems can lead to unintended and undesirable outcomes from these policies.

On October 12–13, 2015 a workshop funded by the National Science Foundation (NSF) was held at Iowa State University in Ames, Iowa with a goal of identifying research needs related to coupled economic and biophysical models within the Food-Energy-Water (FEW) system. 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 NSF’s Social, Behavioral & Economic Sciences (SBE) research needs while also including the critical connectivity needed between social sciences and other disciplines.

The workshop identified two overarching roles for SBE 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, a highly stylized schematic for an integrated assessment model (IAM) of the FEW system. The top level represents human agent behavior (economic decisions, policies, and institutions), which directly affects a wide range of physical and natural systems that produce outputs of value to humans. The second level depicts models for those physical and natural systems. Finally, extensive economics studies have also addressed market impacts and valuation of ecosystem services that comprise the lower layer of the IAM. The diagram highlights the need for an integrated approach that accounts for crucial links between natural systems and human decisions, policies, and values.

While economists have developed extensive research to study the behavior of economic agents and policymakers 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 have rarely been linked to rigorous economic treatments. 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.

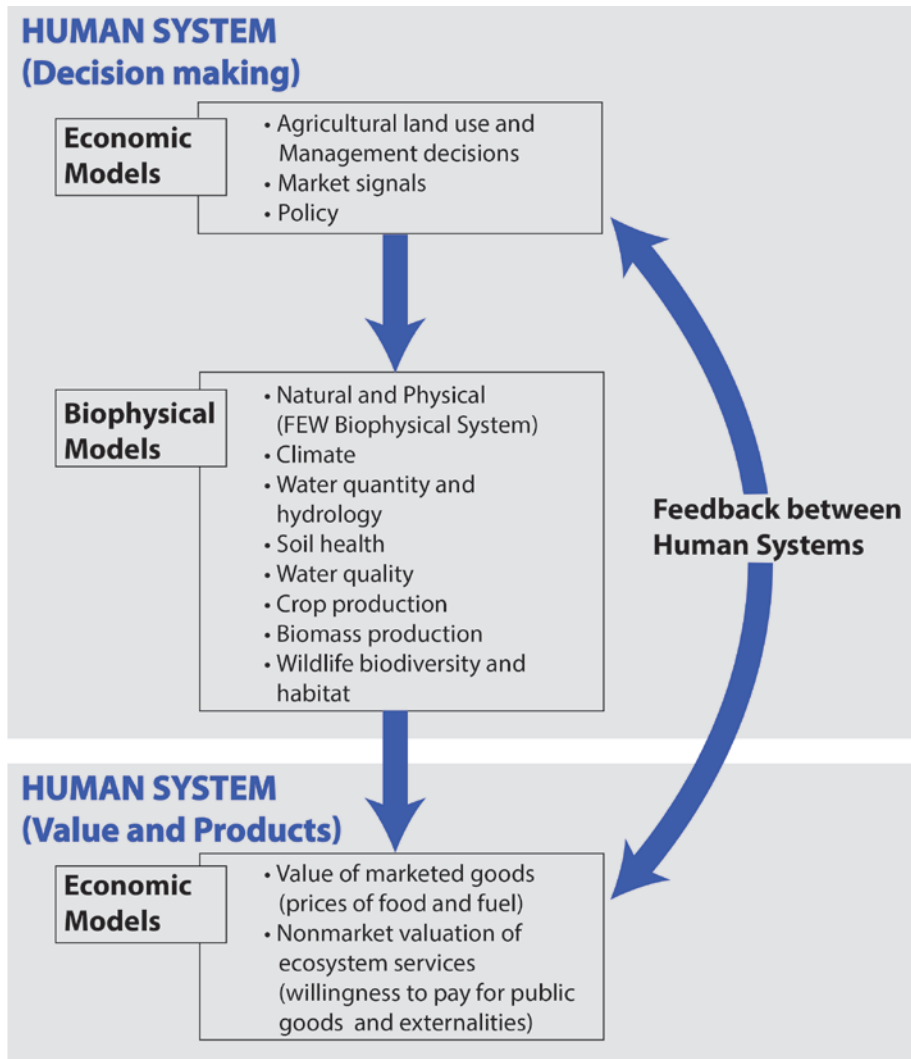


Figure 1. The food, energy, and water nexus: a simple schematic of complete integrated assessment models.

Second, 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, such decision-making is often taken to be random or irrational in linked models, or 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; models of fishery population dynamics that assume fishing pressure is uniform across the stock ignoring obvious 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 egregiously poor policy recommendations.

This white paper summarizes opportunities and challenges for integrated modeling of the FEW system, drawing upon discussions at the workshop as well as prior literature. Section 2 discusses the motivation for integrated assessment modeling of the FEW nexus rather than considering system components separately. This is followed by an overview of models for components of the FEW system, including improvements needed in those models. Section 4 then describes the advances that will be needed for improved integration of FEW components. We conclude with a summary and specific recommendations for advancing integrated modeling of the FEW nexus.

## 2 Importance of developing integrated assessment models of the FEW 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 CO<sub>2</sub> 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 massive diversion of corn into the energy system was having important impacts on corn prices and production, and through global markets, on the production of other crops. Searchinger et al. (2008), were among the first to attract wide attention to the market-mediated global impact of US biofuel policies. Ensuing work somewhat softened some of these results, but not the insight on the need to consider the implications beyond local systems. While the land-use changes predicted differ widely among modeling systems and approaches (reflecting large uncertainties still remaining), Hertel et al. (2010) estimate that these market-mediated linkages resulted in conversion of more than 4 million hectares of pastures and forests to cropland in the rest of the world. As a result, the initial reduction in greenhouse gas emissions (GHGs) 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 expansion of irrigated crops is restricted in regions already experiencing physical water scarcity, terrestrial carbon releases rise by 25 percent. 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-fleshed out FEWS framework (Liu et al., 2015). The diverging results obtained by different modeling groups and systems calls attention to the need for renewed efforts in this field.

In addition to unintended consequences from 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. To capture unintended effects of policy requires that we understand human responses to policy as well as 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 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 multi-criteria 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 tradeoffs 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 provide habitat for grassland birds, reduce soil erosion, and improve 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.

One of the core challenges 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.” On the other hand a tractable integrated model often requires simplified forms of one or more component models, an approach commonly referred to as a “reduced-form” model. (See Box 1 for a summary of the contrast between structural and reduced-form models.) In the following section we briefly overview the core model components for an integrated assessment model of the FEW system, including comments on differing methodologies and levels of detail.

### 3 Summary of modeling capabilities for individual components of the FEW system

#### 3.1 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, accounting for genetics, management, climate, and soil characteristics. These structural models often provide information not only on crop yield but also on 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

#### Box 1: A Note on Terminology

In the workshop presentations and throughout discussion, an issue that regularly arose is the many different terms that scientists use to refer to similar modeling approaches. For purposes of this white paper, we will generally use the term “structural model” to refer to approaches that define underlying technologies and processes and/or explicitly define decision making rules. In some disciplines, models of this type are more commonly referred to as process-based models or mechanistic models. In contrast, we use the term “reduced form” to refer to approaches that do not explicitly define technology, decision rules or physical processes. Other terms commonly used to refer to these models are statistical, econometric, or data-driven methods.

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 at present 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). Like 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, while 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 in order to address issues such as the influence of climate change on agricultural production. It is noteworthy that AgMIP includes economic modeling as an integral component. AgMIP has used economic modeling to address issues such as 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 very detailed panel datasets 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 and Roberts, 2009).

### **3.2 Economic models of land use**

In their simplest form, economic models of land use explain or predict for what purpose a parcel of land will be used based on characteristics of the land 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 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, climate, etc., 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 categorized broadly into two categories: structural models and reduced-form models (See Box 1.) Other categorizations are possible, for instance whether models are static or dynamic, or whether they are partial or general equilibrium models (Khanna and Zilberman, 2012). Partial equilibrium models consider a single market (typically corresponding to a specific geographical area) while 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 GTAP (Randhir and Hertel, 2000), the BLS model (Rosenzweig and Parry, 1994), or constrained linear programming representations of production possibilities (Adams et al., 1990; McCarl and 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 (Plantinga, Mauldin, and Miller, 1999; Stavins, 1999; Pautsch et al., 2001; Searchinger et al., 2008).

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 and Howitt, 2014). However, these models may be poorly identified in an econometric sense (Paris and Howitt, 1998), are typically limited in their ability to capture unobserved, idiosyncratic factors affecting land-use decisions, and adequate micro-level production cost data may not be available. In contrast, reduced-form models have the advantage of implicitly capturing economically relevant factors (Stavins, 1999; Plantinga, Mauldin, and Miller, 1999). In addition, the fact that the technology is implicit 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. This limits the types of inference that can be made from such models, for instance when environmental outcomes are highly dependent on endogenous input application rates. Similarly, this approach can be difficult to generalize to large-scale empirical settings where many alternative land uses are possible. It has so far mostly been implemented in geographically limited regions, or in settings with a small number of alternative land uses or crop management practices.

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 non-linear programming approach (for a recent review, see Mérel and Howitt, 2014).

### **3.3 Water quality models**

Dozens of water quality models have been developed to assess the transport of one or more pollutants over various landscapes and in stream systems, at a specific scale or a range of scales (e.g., Borah et al., 2006; Daniel et al., 2011; Bouraoui and Grizzetti, 2014; Gao and Li, 2014; de Brauwere, 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 et al., 1998, 2012; Arnold and Forher, 2005; 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 (ANNs) (e.g., Gazzaz et al., 2012; Jiang et al., 2013) and statistical approaches such as the SPATIally Referenced Regressions On Watershed attributes (SPARROW) model (Smith et al., 1997; Preston, Alexander, and Wolock, 2011; Schwarz et al., 2011; LaBeau et al., 2014; McLellan et al., 2015). 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-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.<sup>2</sup> SWAT has been successfully used across a wide range of watershed scales (ranging from <1 km<sup>2</sup> to entire continents), environmental conditions, and types of applications as documented in review studies (Arnold and Forher, 2005; Krysanova and Arnold, 2008; Douglas-Mankin, 2010; Tuppad et al., 2011; Gassman et al., 2007, 2014; Gassman, Sadeghi, and Srinivasan, 2014; Bressiani et al., 2015; Gassman and Wang, 2015; Krysanova and White, 2015).

Reduced-form approaches use a statistical model that relates data on water quality outcomes to data on important biophysical and socio-economic 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 mechanistic models. Often the outcome of interest is a measure of water pollution effluent, either from a point source (e.g., an industrial facility that discharges directly into waterways) or a non-point 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 (Earnhart, 2004a, 2004b; Shimshack and Ward, 2008; Cohen and Keiser, 2015). Monthly plant-level panel data on effluent allow researchers to leverage research designs that separate out 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 and Gronberg, 2012), the US Clean Water Act (Smith and Wolloh, 2012; Keiser and Shapiro, 2015), fracking activities (Olmstead et al., 2013), transboundary pollution (Sigman, 2002, 2005; Limpscomb and Mobarak, 2014), and other water pollution regulations abroad (Greenstone and 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. A final set of studies use human responses as the outcome of interest to measure the effects of a water quality policy. These approaches examine how water quality affects use, but may be limited in terms of water quality data and thus directly measure the impacts of a policy on economic uses (e.g., hedonic studies that focus on changes in housing values as a function of a policy change and not directly pollution).

An example of a model that combines both reduced-form and structural approaches is the SPARROW model. The SPARROW 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 in size from tens of km<sup>2</sup> to entire river basin systems that drain large portions of continents (Smith et al., 1997; Preston et al., 2009). This statistical approach is constrained by

---

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

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 (McLellan et al., 2015).<sup>3</sup>

### **3.4 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 recognizes their joint dependence on scarce land and water resources. A large number of 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, and Crago, 2014; Khanna and Zilberman, 2012). 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 (Housh et al., 2015; Chen et al., 2014).

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 often can be grown on low quality land, and can 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 greenhouse gas 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 multi-dimensional effects of food and energy production (Housh et al., 2014).

### **3.5 Research Needs and Challenges**

From presentations at the workshop and follow up discussions, a number of challenges within individual modeling components of the FEW system became apparent. The following items were identified as particularly important.

---

<sup>3</sup> Additional resources regarding documentation or applications of SPARROW can be accessed at <http://water.usgs.gov/nawqa/sparrow/>.

### **3.5.1 Need for increased modeling capacity to represent a wide set of land-use options, biophysical processes, crops, and environmental impacts**

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. Numerous other examples were cited during the workshop, including the need for land use, crop, and water quality models that appropriately represent the movement of nutrients and water through tile drains in agricultural landscapes, in-stream sediment and nutrient processes in rivers and streams, adequate representation of wetlands in water quality models, the impacts of conservation practices on crop yields, and many others.

Existing models have tended to examine strategies to address environmental problems individually. However, FEW systems often generate multiple environmental impacts, some of which occur as complements, such that addressing one leads to co-benefits 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).

### **3.5.2 Need for economic land-use models to incorporate adaptation behavior**

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 (Mendelsohn et al., 1994; 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. Further, 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 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.

### **3.5.3 Need for models to incorporate dynamic and non-neoclassical economic behavior that are tractable for integration with other FEW system models**

IAMs 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 since

computationally it is often infeasible to solve for a dynamic market equilibrium. However, there are situations in which these assumptions are too limiting to accurately reflect underlying behavior.

Zhao (2015) develops an irrigation technology adoption model that relaxes these assumptions by allowing farmers to decide dynamically 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). Previous research has found that non-economic 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 western Lake Erie basin is strongly linked with adoption of filter strips and timing-related phosphorus practices (Howard and Roe, 2013; Wilson et al., 2014). Accounting for such non-optimizing behavior approaches that augment traditional dynamic optimization models is an important research need.

### **3.5.4 Need for model improvements and approaches to incorporating national and international market responses into regional analysis**

It is often natural to study the FEW system at the level of a watershed, as this is the level at which land, water, energy, and food production are 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 (Konar et al., 2013; Dalin et al., 2012; Hoekstra and Mekonnen, 2012). 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 (Teheripour et al., 2013; Hertel et al., 2010; Elobeid et al., 2013a; Fabiosa et al., 2010; Hayes et al., 2009). 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, Burke, and Lobell, 2010).

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 and 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.

## **4 Integrating model components to create Integrated Assessment Models**

### **4.1 Overview**

Using simulation models for prospective analysis of FEW systems requires integrating models describing disparate components of the system. These models are often developed for modeling individual features of the natural system, such as crop growth models for multiple crops, biogeochemical cycles, hydrology, and land-use change. Ensuring system-wide consistency in underlying system boundaries and assumptions and scale of analysis across these diverse models

is critical for meaningful model integration. Validating not only the individual component models but the entire systems-of-systems models by comparing model outcomes with observed reality is important for credible projections using these models. One of the limitations of current modeling approaches is that models incorporating detailed location-specific information tend to cover a smaller geographic area (such as a watershed), while those that have a global scope are highly aggregated and disregard heterogeneity at smaller scales. Developing approaches to link models at different scales, by downscaling outcomes from global to local models and upscaling from local to global models, so that these models operate together could keep component models tractable and yet provide outcomes at both local and global scales.

A fundamental challenge in the development of integrated assessment models 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 and Zilberman (2000) provide a stylized dynamic economic model of phosphorus management that retains model tractability by simplifying the environmental dimension (see Goetz and Zilberman, 2000; Iho, 2010; Iho and Laukkanen, 2012; Xabadia et al., 2006; Xabadia et al., 2008, as well). Their model permits analytical tractability, but ignores realistic features of agricultural landscapes and hydrological processes that imply more complicated nutrient dynamics in soils (Knapp and 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 streamflows 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 SWAT or other detailed representations simplify the economic behavioral model. Farmers are typically assumed to have myopic expectations and make current cropping and land management decisions based on current, and possibly past, conditions. For example, many SWAT models of Lake Erie agroecosystems (Bosch et al., 2013) assume the amount and location of conservation practice adoption and ignore individual farmers' responses to policies and the resulting adoption decisions at the landscape scale.

Innovations are needed to better incorporate dynamic aspects of economic behavior into integrated models that are "realistic enough" in their representation of component processes. Identifying a parsimonious set of variables critical for both the economic and biophysical models is challenging yet essential to reduce model dimensionality. In this regard, it is critical to assess the trade-offs of more or less detail in representation of any particular economic or biophysical process. Lastly, it is important to recognize, quantify, and then minimize the aggregation bias and efficiency loss due to differing spatial scales at which economic and biophysical processes operate.

The right trade-off between model tractability and realism will depend on the research goals. Integrated assessment models often are 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. Agent-based modeling provides a potential approach to represent this behavior in a simulation-based modeling environment (Farmer and Foley, 2009). For example, 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.

On the other hand, 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. While such models are still in their infancy, dynamic renewable resource models provide a useful illustration of this approach (Gopalakrishnan et al., 2011; Landry and Hindsley, 2011; Ranson and Stavins, 2015).

## **4.2 Additional research needs and challenges**

Participants at the workshop identified several challenges and opportunities 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. These issues fall under the following general headings, which we discuss separately.

- Consistency of the component models in terms of scale, regional coverage, and inputs and outputs at system boundaries.
- Providing consistent, internally consistent, and disaggregate datasets.
- Individual disciplines and models differ in how they incorporate statistical uncertainty, making integration difficult.
- There is no clear consensus on the appropriate methods for evaluating and aggregating individual models.
- There are few reduced-form studies that comprehensively evaluate integrated models of the FEW system using historical data with minimal additional assumptions.

### **4.2.1 Consistency of the component models in terms of scale, regional coverage, and inputs and outputs at system boundaries**

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. While the need for this spatial and temporal compatibility is appreciated, there is little consensus on 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 mg/l 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 (say) 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.

#### **4.2.2 Providing spatially and internally consistent disaggregate datasets**

Quantitative analysis of the FEW system requires that the underlying data describing the biophysical and economic systems be internally consistent. In contrast, the 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. Thus, special effort must be made to render these data amenable for use in economic models. The problem is further complicated by the need for considerable geospatial detail in order 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. Since there are currently no consistent global, temporally varying peer-reviewed data bases 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 impacts of climate change on agricultural productivity, among others (Hertel et al., 2010).

In general, the problem of data reconciliation for FEWS can be viewed as constructing consistent data from a diverse array of administrative units, such as counties, states, and nations. (Song et al., 2015). Most of the gridded data currently used in FEWS 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. Since the assumptions feeding into these different data models are often inconsistent (e.g., political boundaries, seasonality, cropping intensity, etc.), the gridded data available for FEWS analysis are also inconsistent and researchers often must perform additional ad hoc adjustments. Such a mechanistically reconciled data base does not ensure fidelity with the underlying source data and there is no clear way to incrementally improve on the final data sets since the entire process is not replicable. 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 and Villoria, 2014).

Additional data collection is highly important as well, which typically involves surveying landowners (recent examples include Fleming, Lichtenberg, and Newburn, 2015, and Gonzalez-Ramirez, Kling, and Arbuckle, 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 datasets, interdisciplinary planning is needed at the survey design stage.

### 4.2.3 Individual disciplines and models differ in how they incorporate statistical uncertainty, evaluation, and aggregation, making integration difficult

An organizing theme in the workshop is the issue of structural modeling approaches as opposed to reduced-form approaches. Models in the first category tend to use detailed scientific knowledge of the systems to represent the systems' underlying structures. The data used in these models typically come from a variety of different data sources and often incorporate data from several experiments. Section 3 of this document gives several examples of these models.

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 document. 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 estimation from a statistical or econometric perspective. Conversely, the reduced-form models typically will not have as rich 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. Where possible, this approach should be pursued aggressively. Many of the individual models discussed earlier in the paper 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, and would greatly facilitate integrating those aspects with the rest of the FEW system. There are many cases, however, where 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 and Sargent's (2007, 2008, 2014) Robust Control framework to add uncertainty over specific modeling assumptions in the DICE model (Nordhaus and Boyer, 2000; Nordhaus, 2008). The robust control approach has been developed for macroeconomic applications and additional research is likely to be necessary before it, or alternative strategies, would be widely applicable in other contexts.<sup>4</sup>

---

<sup>4</sup> 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



In the same vein, methods should 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. (See Kilian, 2013, for a recent and accessible 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). We are unaware of research on the FEW system that tries to add identification or partial identification strategies to a reduced-form econometric model, but those strategies could be especially informative because the underlying scientific processes are much better understood than in macroeconomics.

#### **4.2.4 There is no clear consensus on the appropriate methods for evaluating and aggregating individual models**

A similar tension arises from differential methods across fields for evaluating, selecting, and aggregating models. Participants at the workshop identified “out-of-sample” evaluation methods, where models are scored based on their accuracy in making predictions on a new dataset, as especially promising. A focus on out-of-sample prediction accuracy is likely to have positive spillovers regarding some of the challenges already discussed: since 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.<sup>5</sup> Moreover, by focusing on out-of-sample accuracy, researchers are explicitly aiming to improve the aspect of their models that matter for economic decision-making (Elliott and Timmermann, 2008). Finally, out-of-sample tests of “forecast encompassing” or misspecification (Harvey, Leybourne, and Newbold, 1998) can identify areas that the models can be improved, instead of simply testing whether it outperforms 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 and Mariano, 1995; West, 1996). In addition, there are technical constraints that can make direct comparison of models awkward. (See Clark and McCracken, 2013, for an overview of this literature.) Additional research to develop appropriate out-of-sample tests for the full class of models used in the FEW system is needed before these methods can be widely used.

Moreover, modelers and policymakers 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

---

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.

<sup>5</sup> The implicit danger is that models may focus on predicting variables that are easy to observe, whether or not that variable is fundamentally important.

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. Policymaking in the FEW system will be more effective if policy makers understand the range of potential outcomes rather than just the expected outcome, and 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.<sup>6</sup> Colloquially, the models should aim to predict what might happen, rather than what will happen.

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 and Granger (1969) in economics (Timmermann, 2006, and Elliott and Timmermann, 2008, give 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 there is no single “best” model for such a complex, coupled nonlinear system (e.g., Gleckler et al., 2008; Mearns et al., 2013). 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 exist.

#### **4.2.5 There are few “reduced-form” studies that comprehensively evaluate integrated models of the FEW system using historical data with minimal additional assumptions**

A critical need for validating IAMs is to test predictions of these models with reduced-form empirical approaches. The out-of-sample analyses discussed in the previous section are often performed with an eye towards 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. In order 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 upon assumptions governing these responses. Reduced-form methods that rely upon 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, one could perform *ex post* studies on policies such as the Conservation Reserve Program

---

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

(CRP) to validate one or many steps in the IAM. 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 CRP acreage and changes in water quality. The selection into CRP could potentially be controlled for by taking advantage of somewhat arbitrary cutoffs that govern CRP selection (e.g., one might compare effects from two parcels of land with similar environmental benefit index scores where the two parcels are just on opposite sides of a funding threshold). 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. It is important to note that these methods themselves rely upon their own set of assumptions (e.g., identifying arguably valid counterfactual units of observation). 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.

## 5 Summary and final recommendations

We have identified several major gaps in existing scientific knowledge that present substantial impediments to understanding the FEW system. We especially recommend research in these areas as a priority for future funding:

### 1. Economic models of decision-making in coupled systems

Deliberate human activity has been the dominant factor driving environmental and land-use changes for hundreds of years. While economists have made great strides in modeling and understanding these choices, the coupled systems modeling literature, with some important exceptions, has not reflected these contributions. Several paths forward seem fruitful. First, baseline economic models that assume rationality can be used much more widely than they are currently. Moreover, the current generation of IAMs that include rational agents have emphasized partial equilibrium studies appropriate for smaller systems. To allow this approach to be used to study larger systems, the potential for (and consequences of) general equilibrium effects should be studied as well.

Second, it is important to address shortcomings in these models of economic decision-making. Valuable improvements could be gained from developing coupled models that draw insights from behavioral economics. Many 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. Improved models of human adaptation and induced technological change can also be incorporated into coupled models. Particularly for medium to long-run models, decisions about adaptation and technological change will have substantial effects on the conclusions and policy implications, but more compelling methods for incorporating these changes into modeling are sorely needed. In addition, some economic decisions are intrinsically dynamic yet few coupled models explicitly incorporate

dynamic models. Economic models that address uncertainty in decision making are also underutilized in coupled models of the FEW system.

## **2. Coupling models across disciplines**

Despite much recent progress, established models for one component of the FEW system often cannot currently produce outcomes that can be used as inputs for models of other components. This misalignment makes integrated modeling difficult and is especially apparent in linking models of natural phenomena with models of economic decision-making. Economic agents typically act to maximize a form of utility or welfare that is not directly linked to physical processes, and they typically require probabilistic forecasts as an input to their decision-making that many models in the natural sciences cannot directly produce.

We believe that an especially promising approach is the development of “bridge” models that convert outputs from one model into inputs for another. Such models can be viewed as application-specific, reduced-form distillations of a richer and more realistic underlying model. Ideally, these bridge models would be developed in collaborative research projects involving economists, statisticians, and disciplinary specialists, and would contribute to improved understanding in the scientific discipline as well.

## **3. Model validation and comparison**

There is little clarity on how models should be evaluated and compared to each other, 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 the models’ out-of-sample distributional forecasting performance, as well as that of the IAM overall, is especially promising and of particular importance.

Moreover, applications of IAMs tend to estimate the effect of hypothetical future policy actions, but there have been very few studies that have used these models to estimate the effect of past policy actions. These exercises should be encouraged. 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.

## References

- Adams, R.M., C. Rosenzweig, R.M. Peart, J.T. Ritchie, B.A. McCarl, J.D. Glycer, R.B. Curry, J.W. Jones, K.J. Boote, and L.H. Allen. 1990. "Global Climate Change and US Agriculture." *Nature* 345: 219–224.
- Antle, J.M., and R.O. Valdivia. 2006. "Modelling the Supply of Ecosystem Services from Agriculture: A Minimum-data Approach." *Australian Journal of Agricultural and Resource Economics* 50(1): 1–15.
- Antle, J.M., and S.M. Capalbo. 2001. "Econometric-process Models for Integrated Assessment of Agricultural Production Systems." *American Journal of Agricultural Economics* 83: 389–401.
- Arnold, J.G., D.N. Moriasi, P.W. Gassman, K.C. Abbaspour, M.J. White, R. Srinivasan, C. Santhi, R.D. Harmel, A. van Griensven, M.W. Van Liew, N. Kannan, and M.K. Jha. 2012. "SWAT: Model use, Calibration, and Validation." *Transactions of the ASABE* 55(4): 1491–1508. doi: 10.13031/2013.42256.
- Arnold, J.G., and N. Fohrer. 2005. "SWAT2000: Current Capabilities and Research Opportunities in Applied Watershed Modeling." *Hydrological Processes* 19(3): 563–572. doi: 10.1002/hyp.5611.
- Arnold, J.G., R. Srinivasan, R.S. Muttiah and J.R. Williams. 1998. "Large Area Hydrologic Modeling and Assessment Part I: Model Development." *Journal of the American Water Resources Association* 34(1): 73–89. doi: 10.1111/j.1752-1688.1998.tb05961.x.
- Bates, J.M., and C.W. Granger. 1969. "The Combination of Forecasts." *Operational Research Quarterly* 20(4): 451–468.
- Berger, T., and C. Troost. 2014. "Agent-based Modelling of Climate Adaptation and Mitigation Options in Agriculture." *Journal of Agricultural Economics* 65(2): 323–348.
- Borah, D.K., G. Yagow, A. Saleh, P.L. Barnes, W. Rosenthal, E.C. Krug, and L.M. Hauck. 2006. "Sediment and Nutrient Modeling for TMDL Development and Implementation." *Transactions of the ASABE* 49(4): 967–986. doi: 10.13031/2013.21742.
- Bosch, N.S., et al. 2013. "Scenario-testing of Agricultural Best Management Practices in Lake Erie Watersheds." *Journal of Great Lakes Research* 39: 429–436.
- Bouraoui, F., and B. Grizzetti. 2014. "Modelling Mitigation Options to Reduce Diffuse Nitrogen Water Pollution from Agriculture." *Science of the Total Environment* 468–469: 1267–1277. doi: 10.1016/j.scitotenv.2013.07.066.

- Bressiani, D.D.A., P.W. Gassman, J.G. Fernandes, L.H.P. Garbossa, R. Srinivasan, N.B. Bonumá, and E.M. Mendiondo. 2015. "A Review of Soil and Water Assessment Tool (SWAT) Applications in Brazil: Challenges and Prospects." *International Journal of Agricultural and Biological Engineering* 8(3): 9–35. doi: 10.3965/ij.ijabe.20150803.1765.
- Britz, Wolfgang, and Thomas W. Hertel. 2011. "Impacts of EU Biofuels Directives on Global Markets and EU Environmental Quality: An Integrated PE, Global CGE Analysis." *Agriculture, Ecosystems and Environment* 142(1–2): 102–109. doi:10.1016/j.agee.2009.11.003.
- Cantelaube, P., P.A. Jayet, F. Carre, C. Bamps, and P. Zakharov. 2012. "Geographical Downscaling of Outputs Provided by an Economic Farm Model Calibrated at the Regional Level." *Land Use Policy* 29(1): 35–44.
- Carpenter, S.R., D. Ludwig, and W.A. Brock. 1999. "Management of Eutrophication for Lakes Subject to Potentially Irreversible Change." *Ecological Applications* 9: 751–771.
- Chen, X, H. Huang, M. Khanna, and H. Önal. 2014. "Alternative Fuel Standards: Welfare Effects and Climate Benefits." *Journal of Environmental Economics and Management* 67: 241–257.
- Chen, X., and H. Önal. 2012. "Modeling Agricultural Supply Response Using Mathematical Programming and Crop Mixes." *American Journal of Agricultural Economics* 94: 674–686.
- Chen, Y., and S. Yang. 2007. "Estimating Disaggregate Models using Aggregate Data through Augmentation of Individual Choice." *Journal of Marketing Research* 44(4): 613–621.
- Clark, T.E., and M.W. McCracken. 2013. "Advances in Forecast Evaluation." In *Handbook of Economic Forecasting, Vol. 2*. Elsevier: North-Holland.
- Cohen, Alex, and David A. Keiser. 2015. "The Effectiveness of Overlapping Pollution Regulations: Evidence from the Ban on Phosphate in Dishwasher Detergent." Working paper no. 14034. Iowa State University.
- Corradi, V., and Swanson, N.R., 2006. "Predictive Density Evaluation." *Handbook of Economic Forecasting* 1: 197–284.
- Costinot, A., D. Donaldson, and C. Smith. 2014. "Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World." NBER Working Paper no. 20079.
- Dalin, Carole, Megan Konar, Naota Hanasaki, Andrea Rinaldo, and Ignacio Rodriguez-Iturbe. 2012. "Evolution of the Global Virtual Water Trade Network." *Proceedings of the National Academy of Sciences* 109(16): 5989–94. doi:10.1073/pnas.1203176109.

- Daniel, E.B., J.V. Camp, E.J. LeBoeuf, J.R. Penrod, J.P. Dobbins and M.D. Abkowitz. 2011. "Watershed Modeling and its Applications: A State-of-the-Art Review." *The Open Hydrology Journal* 5: 26–50. doi: 10.2174/1874378101105010026.
- de Brauwere, A., N.K. Ouattara, and P. Servais. 2014. "Modeling Fecal Indicator Bacteria Concentrations in Natural Surface Waters: A Review." *Critical Reviews in Environmental Science and Technology* 44: 2380–2453. doi: 10.1080/10643389.2013.829978.
- Diebold, F.X. 2015. "Comparing Predictive Accuracy, Twenty Years Later: A Personal Perspective on the Use and Abuse of Diebold–Mariano Tests." *Journal of Business and Economic Statistics* 33(1) 1–1.
- Diebold, F.X., and R.S. Mariano. 1995. "Comparing Predictive Accuracy." *Journal of Business and Economic Statistics* 13(3): 253–263.
- Douglas-Mankin, K.R., R. Srinivasan, and J.G. Arnold. 2010. "Soil and Water Assessment Tool (SWAT) Model: Current Developments and Applications." *Transactions of the ASABE* 53(5): 1423–1431. doi: 10.13031/2013.34915.
- Earnhart, Dietrich. 2004a. "Regulatory Factors Shaping Environmental Performance at Publicly-owned Treatment Plants." *Journal of Environmental Economics and Management* 48(1): 665–681.
- Earnhart, Dietrich. 2004b. "Panel Data Analysis of Regulatory Factors Shaping Environmental Performance." *The Review of Economics and Statistics* 86(1): 391–401.
- Elobeid, A., M. Carriquiry, J. Dumortier, F. Rosas, K. Mulik, J. F. Fabiosa, D. J. Hayes, and B. A. Babcock. 2013a. "Biofuel Expansion, Fertilizer Use and GHG Emissions: Unintended Consequences of Mitigation Policies." *Economics Research International* 2013: (12 pages).
- Elobeid, A., S. Tokgoz, R. Dodder, T. Johnson, O. Kaplan, L. Kurkalova, and S. Secchi. 2013b. "Integration of Agricultural and Energy System Models for Biofuel Assessment." *Environmental Modelling and Software* 48: 1–16.
- Elliott, G., and A. Timmermann. 2008. "Economic Forecasting." *Journal of Economic Literature* 46(1): 3–56.
- Fabiosa, J.F., J. C. Beghin, F. Dong, A. Elobeid, S. Tokgöz, and T. Yu. 2010. "Land Allocation Effects of the Global Ethanol Surge: Predictions from the International FAPRI Model." *Land Economics* 86(4): 687–706.
- Farmer, J.D., and D. Foley. 2009. "The Economy Needs Agent-based Modelling." *Nature* 460: 685–686.

- Farrell, A.E. 2006. "Ethanol Can Contribute to Energy and Environmental Goals." *Science* 311: 506–8.
- Fezzi, C., A.R. Harwood, A.A. Lovett, and I.J. Bateman. 2015. "The Environmental Impact of Climate Change Adaptation." *Nature Climate Change* 5: 255–260.
- Fezzi, C., and I.J. Bateman. 2011. "Structural Agricultural Land Use Modeling for Spatial Agro-environmental Policy Analysis." *American Journal of Agricultural Economics* 93(4): 1168–1188.
- Fleming, P., E. Lichtenberg, and D.A. Newburn. 2015. "Agricultural Cost Sharing and Conservation Practices for Nutrient Reduction in the Chesapeake Bay Watershed." Selected Paper, 2015 AAEA Meetings.
- Foley, J.A., S. Levis, M.H. Costa, W. Cramer, and D. Pollard. 2000. "Incorporating Dynamic Vegetation Cover within Global Climate Models." *Ecological Applications* 10: 1620–1632.
- Gao, L., and D. Li. 2014. "A Review of Hydrological/Water-quality Models." *Frontiers of Agricultural Science and Engineering* 1(4): 267–276. doi: 10.15302/J-FASE-2014041.
- Gassman, P.W., A.M. Sadeghi, and R. Srinivasan. 2014. "Applications of the SWAT Model Special Section: Overview and Insights." *Journal of Environmental Quality* 43(1): 1–8. doi: 10.2134/jeq2013.11.0466.
- Gassman P.W., C. Balmer, M. Siemers, and R. Srinivasan. 2014. "The SWAT Literature Database: Overview of Database Structure and Key SWAT Literature Trends." Proceedings of the 2014 International SWAT Conference, July 28–August 1, Pernambuco, Brazil. Texas Water Resources Institute Technical Report – TR-472. Available at: <http://swat.tamu.edu/conferences/2014/>.
- Gassman, P.W., M.R. Reyes, C.H. Green, and J.G. Arnold. 2007. "The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions." *Transactions of the ASABE* 50(4): 1211–1250. doi: 10.13031/2013.23634.
- Gassman, P.W. and Y. Wang. 2015. "IJABE SWAT Special Issue: Innovative Modeling Solutions for Water Resource Problems." *International Journal of Agricultural and Biological Engineering* 8(3): 1–8. doi: 10.3965/j.ijabe.20150803.1763.
- Gazzaz, N.M., M.K. Yusoff, A.Z. Aris, H. Juahir, and M.F. Ramli. 2012. "Artificial Neural Network Modeling of the Water Quality Index for Kinta River (Malaysia) Using Water Quality Variables as Predictors." *Marine Pollution Bulletin* 64(11): 2409–2420. doi: 10.1016/j.marpolbul.2012.08.005.
- Gleckler, P.J., K.E. Taylor, and C. Doutriaux. 2008. "Performance Metrics for Climate Models." *Journal of Geophysical Resources* 113. doi:10.1029/2007JD008972.



- Gneiting, T. and M. Katzfuss. 2014. "Probabilistic Forecasting." *Annual Review of Statistics and Its Application* 1: 125–151.
- Goetz, R.U., and D. Zilberman. 2000. "The Dynamics of Spatial Pollution: The Case of Phosphorus Runoff from Agricultural Land." *Journal of Economic Dynamics and Control* 24: 143–163.
- Gonzalez-Ramirez, M.J., C.L. Kling, and J.G. Arbuckle, Jr. 2015. "Cost-share Effectiveness in the Adoption of Cover Crops in Iowa." Selected Paper, 2015 AAEA Meetings.
- Gopalakrishnan, S., et al. 2011. "The Value of Disappearing Beaches: A Hedonic Pricing Model with Endogenous Beach Width." *Journal of Environmental Economics and Management* 61: 297–310.
- Hansen, Lars Peter, and Thomas J. Sargent. 2007. "Recursive Robust Estimation and Control without Commitment." *Journal of Economic Theory* 136(1): 1–27.
- Hansen, Lars Peter, and Thomas J. Sargent. 2008. *Robustness*. Princeton: Princeton University Press.
- Hansen, Lars Peter, and Thomas J. Sargent. 2014. *Uncertainty within Economic Models*. Singapore: World Scientific.
- Harvey, D.I., S.J. Leybourne, and P. Newbold. 1998. "Tests for Forecast Encompassing." *Journal of Business and Economic Statistics* 16(2): 254–259.
- Hayes, D.J., B.A. Babcock, J. Fabiosa, S. Tokgoz, A. Elobeid, T. Yu, F. Dong, C. Hart, E. Chavez, S. Pan, M. Carriquiry, and J. Dumortier. 2009. "Biofuels: Potential Production Capacity, Effects on Grain and Livestock Sectors, and Implications for Food Prices and Consumers." *Journal of Agricultural and Applied Economics* 41(2): 1–27.
- Hendricks, N.P., S. Sinnathamby, K. Douglas-Mankin, A. Smith, D.A. Sumner, and D.H. Earnhart. 2014. "The Environmental Effects of Crop Price Increases: Nitrogen Losses in the US Corn Belt." *Journal of Environmental Economics and Management* 68(3): 507–526.
- Hertel, T., A. Golub, A. Jones, M. O'Hare, R. Plevin, and D. Kammen. 2010. "Effects of US Maize Ethanol on Global Land Use and Greenhouse Gas Emissions: Estimating Market-Mediated Responses." *Bioscience* 60(3) 223–231.
- Hertel, Thomas W., Marshall B. Burke, and David B. Lobell. 2010. "The Poverty Implications of Climate-induced Crop Yield Changes by 2030." *Global Environmental Change* 20(4): 577–585. doi:10.1016/j.gloenvcha.2010.07.001.
- Hertel, T.W, and N.B. Villoria. 2014. "GEOSHARE: Geospatial Open Source Hosting of Agriculture, Resource and Environmental Data for Discovery and Decision Making."

Purdue University.

[https://mygeohub.org/resources/977/download/GEOSHARE\\_Prospectus-Final.pdf](https://mygeohub.org/resources/977/download/GEOSHARE_Prospectus-Final.pdf).

- Hertel, T.W., W. Britz, N.S. Diffenbaugh, N. Ramankutty, and N.B. Villoria. 2010. "A Global, Spatially Explicit, Open Source Data Base for Analysis of Agriculture, Forestry, and the Environment: Proposal and Institutional Considerations." Department of Agricultural Economics, Purdue University.  
[http://www.agecon.purdue.edu/foresight/proposal\\_spatial\\_database10-15-2010.pdf](http://www.agecon.purdue.edu/foresight/proposal_spatial_database10-15-2010.pdf).
- Hoekstra, Arjen Y., and Mesfin M. Mekonnen. 2012. "The Water Footprint of Humanity." *Proceedings of the National Academy of Sciences* 109(9): 3232–37.  
doi:10.1073/pnas.1109936109.
- Hoekstra, Arjen Y., Mesfin M. Mekonnen, Ashok K. Chapagain, Ruth E. Mathews, and Brian D. Richter. 2012. "Global Monthly Water Scarcity: Blue Water Footprints versus Blue Water Availability." *PLoS ONE* 7(2): e32688. doi:10.1371/journal.pone.0032688.
- Housh, M., M. Khanna, and X. Cai. 2015. "Mix of First and Second Generation Biofuels to Meet Multiple Environmental Objectives: Implications for Policy at a Watershed Scale." *Water Economics and Policy* 1(3): 1550006 (26 pages).
- Housh, M., M. Yaeger, X. Cai, G. McIsaac, M. Khanna, M. Sivapalan, Y. Ouyang, I. Al-Qadi, A. Jain. 2015. "Managing Multiple Mandates: A System of Systems Model to Analyze Strategies for Producing Cellulosic Ethanol and Reducing Riverine Nitrate Loads in the Upper Mississippi River Basin." *Environmental Science and Technology* 49(19): 11932–11940.
- Housh, M., X. Cai, T. Ng, G. McIsaac, Y. Ouyang, M. Khanna, M. Sivapalan, A. Jain, S. Eckhoff, S. Gasteyer, I. Al-Qadi, Y. Bai, M. Yaeger, S. Ma, and Y. Song. 2014. "System of Systems Model for Analysis of Biofuel Development." *Journal of Infrastructure Systems* 10.1061/(ASCE)IS.1943-555X.0000238, 04014050.
- Howard, G., and B.E. Roe. 2013. "Stripping Because You Want to Versus Stripping Because the Money is Good: A Latent Class Analysis of Farmer Preferences Regarding Filter Strip Programs." AAEA and CAES Joint Annual Meeting, Washington, D.C. August.
- Hudiburg, T.W., W. Wang, M. Khanna, S.P. Long, P. Dwivedi, W.J. Parton, M. Hartmann, and E.H. DeLucia. Forthcoming. "Impacts of a 32 Billion Gallon Bioenergy Landscape on Land and Fossil Fuel use in the US." *Nature Energy*.
- Iho, A. 2010. "Essays on Socially Optimal Phosphorus Policies in Crop Production." MTT Agrifood Research Finland.
- Iho, A., et al. 2014. "Agri-environmental Auctions for Phosphorus Load Reduction: Experiences from a Finnish Pilot." *Australian Journal of Agricultural and Resource Economics* 58: 205–222.

- Iho, A., and M. Laukkanen. 2012. "Precision Phosphorus Management and Agricultural Phosphorus Loading." *Ecological Economics* 77: 91–102.
- Jayakrishnan, R., et al. 2005. "Advances in the Application of the SWAT Model for Water Resources Management." *Hydrological Processes* 19: 749–762.
- Jiang, Y., Z. Nan, and S. Yang. 2013. "Risk Assessment of Water Quality using Monte Carlo Simulation and Artificial Neural Network Method." *Journal of Environmental Management* 122: 130–136. doi: 10.1016/j.jenvman.2013.03.015.
- Jones, J.W., G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, P.W. Wilkens, U. Singh, A.J. Gijsman, and J.T. Ritchie. 2003. "The DSSAT Cropping System Model." *European Journal of Agronomy* 18: 235–265.
- Keating, B.A., P.S. Carberry, G.L. Hammer, M.E. Probert, M.J. Robertson, D. Holzworth, N.I. Huth, J.N. Hargreaves, H. Meinke, Z. Hochman, and G. McLean. 2003. "An Overview of APSIM, a Model Designed for Farming Systems Simulation." *European Journal of Agronomy* 18: 267–288.
- Keiser, David A., and Joseph S. Shapiro. 2015. "Consequences of the Clean Water Act and the Demand for Water Quality." Mimeo, Iowa State.
- Kenny, G.J., R.A. Warrick, B.D. Campbell, G.C. Sims, M. Camilleri, P.D. Jamieson, N.D. Mitchell, H.G. McPherson, and M.J. Salinger. 2000. "Investigating Climate Change Impacts and Thresholds: An Application of the CLIMFACTS Integrated Assessment Model for New Zealand Agriculture." *Climatic Change* 46: 91–113.
- Key, N., and M.J. Roberts. 2009. "Nonpecuniary Benefits to Farming: Implications for Supply Response to Decoupled Payments." *American Journal of Agricultural Economics* 91(1): 1–18.
- Khanna, M., and D. Zilberman. 2012. "Modeling the Land-use and Greenhouse-gas Implications of Biofuels." *Climate Change Economics* 3: 1250016.
- Khanna, M., D. Zilberman, and C. Crago. 2014. "Modeling Land Use Change with Biofuels." In *Oxford Handbook of Land Economics*, edited by J.M. Duke, and J.J. Wu, chapter 4. Oxford: Oxford University Press.
- Kilian, Lutz. 2013. "Structural Vector Autoregressions." In *Handbook of Research Methods and Applications in Empirical Macroeconomics*, edited by N. Hashimzade and M. Thornton, 515–554. Cheltenham: Edward Elgar.
- Kiniry, J.R., J.D. MacDonald, A.R. Kemanian, B. Watson, G. Putz and E.E. Prepas. 2008. "Plant Growth Simulation for Landscape-scale Hydrological Modelling." *Hydrological Sciences Journal* 53: 1030–1042.

- Knapp, K.C., and K.A. Schwabe. 2008. "Spatial Dynamics of Water and Nitrogen Management in Irrigated Agriculture." *American Journal of Agricultural Economics* 90: 524–539.
- Konar, M., Z. Hussein, N. Hanasaki, D.L. Mauzerall, and I. Rodriguez-Iturbe. 2013. "Virtual Water Trade Flows and Savings under Climate Change." *Hydrology and Earth System Sciences Discussions* 10(1): 67–101. doi:10.5194/hessd-10-67-2013.
- Krysanova V., and M. White. 2015. "Advances in Water Resources Assessment with SWAT—An Overview." *Hydrological Sciences Journal* 60(5): 771–783. doi: 10.1080/02626667.2015.1029482.
- Krysanova, V., and J.G. Arnold. 2008. "Advances in Ecohydrological Modelling with SWAT—a Review." *Hydrological Sciences Journal* 53(5): 939–947. doi: 10.1623/hysj.53.5.939.
- Kurkalova, L.A., and S.S. Rabotyagov. 2006. "Estimation of a Binary Choice Model with Grouped Choice Data." *Economics Letters* 90(2): 170–175.
- Kurkalova, L.A., and T.R. Wade. 2013. "Aggregated Choice Data and Logit Models: Application to Environmental Benign Practices of Conservation Tillage by Farmers in the State of Iowa." *Applied Econometrics and International Development* 13(2): 119–128.
- LaBeau, M.B., D.M. Robertson, A.S. Mayer, B.C. Pijanowskic and D.A. Saad. 2014. "Effects of Future Urban and Biofuel Crop Expansions on the Riverine Export of Phosphorus to the Laurentian Great Lakes." *Ecological Modelling* 277: 27–37. doi: 10.1016/j.ecolmodel.2014.01.016.
- Landry, C.E., and P. Hindsley. 2011. "Valuing Beach Quality with Hedonic Property Models." *Land Economics* 87: 92–108.
- Lawler, Joshua J., David J. Lewis, Erik Nelson, Andrew J. Plantinga, Stephen Polasky, John C. Withey, David P. Helmers, Sebastián Martinuzzi, Derric Pennington, and Volker C. Radeloff. 2014. "Projected Land-use Change Impacts on Ecosystem Services in the United States." *Proceedings of the National Academy of Sciences* 111(20): 7492–7497.
- Lewis, D., A. Plantinga, E. Nelson, and S. Polasky. 2011. "The Efficiency of Voluntary Incentive Policies for Preventing Biodiversity Loss." *Resource and Energy Economics* 33: 192–211.
- Libra, R.D., C.F. Wolter, R.J. Langel. 2004. "Nitrogen and Phosphorus Budgets for Iowa and Iowa Watersheds." Iowa Department of Natural Resources, Iowa Geological Survey. <http://s-iihr34.iihr.uiowa.edu/publications/uploads/Tis-47.pdf>
- Lipscomb, M., and A.M. Mobarak. 2014. "Decentralization and Water Pollution Spillovers: Evidence from the Redrawing of County Boundaries in Brazil." Mimeo, Yale University.

- Liu, Jianguo, Harold Mooney, Vanessa Hull, Steven J. Davis, Joanne Gaskell, Thomas Hertel, Jane Lubchenco, et al. 2015. "Systems Integration for Global Sustainability." *Science* 347 (6225): 1258832. doi:10.1126/science.1258832.
- Liu, Jing, Thomas W. Hertel, Farzad Taheripour, Tingju Zhu, and Claudia Ringler. 2014. "International Trade Buffers the Impact of Future Irrigation Shortfalls." *Global Environmental Change* 29: 22–31. doi:10.1016/j.gloenvcha.2014.07.010.
- Lobell, David B., David Thau, Christopher Seifert, Eric Engle, and Bertis Little. 2015. "A Scalable Satellite-based Crop Yield Mapper." *Remote Sensing of Environment* 164: 324–333.
- Lobell, D.B., M.J. Roberts, W. Schlenker, N. Braun, B.B. Little, R.M. Rejesus, and G.L. Hammer. 2014. "Greater Sensitivity to Drought Accompanies Maize Yield Increase in the US Midwest." *Science* 344: 516–519.
- Lobell, D.B., M. Banziger, C. Magorokosho, and B. Vivek. 2011. "Nonlinear Heat Effects on African Maize as Evidenced by Historical Yield Trials." *Nature Climate Change* 1: 42–45.
- Lotze-Campen, H., M. von Lampe, P. Kyle, S. Fujimori, P. Havlik, H. van Meijl, T. Hasegawa, A. Popp, C. Schmitz, A. Tabeau, H. Valin, D. Willenbockel, and M. Wise. 2014. "Impacts of Increased Bioenergy Demand on Global Food Markets: An AgMIP Economic Model Intercomparison." *Agricultural Economics* 45: 103–116.
- Luckmann, Jonas, Harald Grethe, Scott McDonald, Anton Orlov, and Khalid Siddig. 2014. "An Integrated Economic Model of Multiple Types and Uses of Water." *Water Resources Research* 50(5): 3875–92. doi:10.1002/2013WR014750.
- Manski, C. 1990. "Nonparametric Bounds on Treatment Effects." *American Economic Review Papers and Proceedings* 80: 319–323.
- Manski, C. 1995. *Identification Problems in the Social Sciences*. Cambridge: Harvard University Press.
- McCarl, B.A., and U.A. Schneider. 2001. "Greenhouse Gas Mitigation in U.S. Agriculture and Forestry." *Science* 294: 2481–2482.
- McLellan, E., D. Robertson, K. Schilling, M. Tomer, J. Kostel, D. Smith, and K. King. 2015. "Reducing Nitrogen Export from the Corn Belt to the Gulf of Mexico: Agricultural Strategies for Remediating Hypoxia." *Journal of the American Water Resources Association* 51(1): 263–289. doi: 10.1111/jawr.12246.
- Mearns, L.O., R. Arritt, S. Biner, M.S. Bukovsky, S. McGinnis, S. Sain, D. Caya, J. Correia Jr, D. Flory, W. Gutowski, and E.S. Takle. 2012. "The North American Regional Climate Change Assessment Program: Overview of Phase I Results." *Bulletin of the American Meteorological Society* 93(9): 1337–1362.

- Mérel, P., and R. Howitt. 2014. “Theory and Application of Positive Mathematical Programming in Agriculture and the Environment.” *Annual Review of Resource Economics* 6: 451–470.
- Miller, D.J., and A.J. Plantinga. 1999. “Modeling Land Use Decisions with Aggregate Data.” *American Journal of Agricultural Economics* 81(1): 180–194.
- Nair, S.S., K.W. King, J.D. Witter, B.L. Sohngen, and N.R. Fausey. 2011. “Importance of Crop Yield in Calibrating Watershed Water Quality Simulation Tools.” *Journal of the American Water Resources Association* 47: 1285–1297. doi: 10.1111/j.1752-1688.2011.00570.x
- National Research Council. 2014. *Advancing Land Change Modeling: Opportunities and Research Requirements*. Washington, D.C.: The National Academies Press. doi:10.17226/18385
- Ng, T.L., et al. 2011. “An Agent-based Model of Farmer Decision-making and Water Quality Impacts at the Watershed Scale under Markets for Carbon Allowances and a Second-generation Biofuel Crop.” *Water Resources Research* 47(9). doi: 10.1029/2011WR010399.
- Nordhaus, William D. 2008. *A Question of Balance: Weighing the Options on Global Warming Policies*. New Haven: Yale University Press.
- Nordhaus W.D., and J. Boyer. 2000. *Warming the World: Economic Models of Global Warming*. Cambridge: MIT Press.
- Olmstead, S.M., L.A. Muehlenbachs, J.-S. Shih, Z. Chu, and A.J. Krupnick. 2013. “Shale Gas Development Impacts on Surface Water Quality in Pennsylvania.” *Proceedings of the National Academy of Sciences* 110(13): 4962-4967.
- Paris, Q., and R.E. Howitt. 1998. “An Analysis of Ill-Posed Production Problems Using Maximum Entropy.” *American Journal of Agricultural Economics* 80: 124–138.
- Pautsch, G., L. Kurkalova, B.A. Babcock, and C. Kling. 2001. “The Efficiency of Sequestering Carbon in Agricultural Soils.” *Contemporary Economic Policy* 19: 123–134.
- Pelikan, Janine, Wolfgang Britz, and Thomas W. Hertel. 2015. “Green Light for Green Agricultural Policies? An Analysis at Regional and Global Scales.” *Journal of Agricultural Economics* 66(1): 1–19. doi:10.1111/1477-9552.12065.
- Plantinga, A.J. 2015. “Integrating Economic Land-Use and Biophysical Models.” *Annual Review of Resource Economics* 7: 233–249.
- Plantinga, A.J., T. Mauldin, and D.J. Miller. 1999. “An Econometric Analysis of the Costs of Sequestering Carbon in Forests.” *American Journal of Agricultural Economics* 81: 812–824.

- Preston, S.D., R.B. Alexander, and D.M. Wolock. 2011. "Sparrow Modeling to Understand Water-quality Conditions in Major Regions of the United States: A Featured Collection Introduction." *Journal of the American Water Resources Association* 47(5): 887–890. doi: 10.1111/j.1752-1688.2011.00585.x.
- Preston, S.D., R.B. Alexander, M.D. Woodside, and P.A. Hamilton. 2009. "SPARROW MODELING—Enhancing Understanding of the Nation's Water Quality." Fact Sheet 2009–3019. U.S. Geological Survey, U.S. Department of the Interior.
- Randhir, T.O., and T.W. Hertel. 2000. "Trade Liberalization as a Vehicle for Adapting to Global Warming." *Agricultural and Resource Economics Review* 29: 159–172.
- Ranson, M., and R.N. Stavins. 2015. "Linkage of Greenhouse Gas Emissions Trading Systems: Learning from Experience." *Climate Policy* 1–17.
- Rosegrant, Mark W., Claudia Ringler, Tingju Zhu, Simla Tokgoz, and Prapti Bhandary. 2013. "Water and Food in the Bioeconomy: Challenges and Opportunities for Development." *Agricultural Economics* 44(s1): 139–50. doi:10.1111/agec.12058.
- Rosenzweig, C., and M.L. Parry. 1994. "Potential Impact of Climate Change on World Food Supply." *Nature* 367: 133–138.
- Rosenzweig, C., J.W. Jones, J.L. Hatfield, A.C. Ruane, K.J. Boote, P. Thorburn, J.M. Antle, G.C. Nelson, C. Porter, S. Janssen, S. Asseng B. Basso, F. Ewert, D. Wallach, G. Baigorria, and J.M. Winter. 2013. "The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and Pilot Studies." *Agricultural and Forest Meteorology* 170: 166–182.
- Rossi, B. 2014. "Density Forecasts in Economics, Forecasting and Policymaking." *Els Opuscles del CREI* 37.
- Rudik, Ivan. 2016. "The Social Cost of Carbon When Damages are Unknown." *SSRN Working Paper*. Available at <http://ssrn.com/abstract=2516632> or <http://dx.doi.org/10.2139/ssrn.2516632>.
- Searchinger, T., R. Heimlich, R.A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T.H. Yu. 2008. "Use of US Croplands for Biofuels Increases Greenhouse Gases through Emissions from Land-use Change." *Science* 319: 1238–1240.
- Segarra, E., et al. 1989. "Nitrogen Carry-over Impacts in Irrigated Cotton Production, Southern High Plains of Texas." *Western Journal of Agricultural Economics* 14(20): 300–309.
- Schlenker, W., and M.J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences of the United States of America* 106(37): 15594–15598.

- Schmitz, C., H. van Meijl, P. Kyle, G.C. Nelson, S. Fujimori, A. Gurgel, P. Havlik, E. Heyhoe, D.M. d'Croze, A. Popp, R. Sands, A. Tabeau, D. van der Mensbrugghe, M. von Lampe, M. Wise, E. Blanc, T. Hasegawa, A. Kavallari, and H. Valin. 2014. "Land-use Change Trajectories up to 2050: Insights from a Global Agro-economic Model Comparison." *Agricultural Economics* 45: 69–84. doi: 10.1111/agec.12090
- Schwarz, G.E., R.B. Alexander, R.A. Smith and S.D. Preston. 2011. "The Regionalization of National-scale SPARROW Models for Stream Nutrients." *Journal of the American Water Resources Association* 47(5): 1151–1172. doi: 10.1111/j.1752-1688.2011.00581.x.
- Shimshack, Jay P., and Michael B. Ward. 2008. "Enforcement and Over-compliance." *Journal of Environmental Economics and Management* 55(1): 90–105.
- Sigman, H. 2002. "International Spillovers and Water Quality in Rivers: Do Countries Free Ride?" *American Economic Review* 92(4): 1152–1159.
- Sigman, H. 2005. "Transboundary Spillovers and Decentralization of Environmental Policies." *Journal of Environmental Economics and Management* 50: 82–101.
- Sims, Christopher A. 1980. "Macroeconomics and Reality." *Econometrica* 48(1): 1–48.
- Smith, R.A., G.E. Schwarz, and R.B. Alexander, 1997. "Regional Interpretation of Water-quality Monitoring Data." *Water Resources Research* 33: 2781–2798. doi: 10.1029/97WR02171.
- Smith, V.K., and C.V. Wolloh. 2012. "Has Surface Water Quality Improved Since the Clean Water Act?" NBER Working paper no. 18192.
- Song, Jingyu, Michael Delgado, Paul V. Preckel, and Nelson B. Villoria. 2015. "Downscaling Land Use Data: Where Do Crops Grow at a Fine Scale?" In progress. Purdue University San Francisco, CA.
- Sprague, L.A., and J.A.M. Gronberg. 2012. "Relating Management Practices and Nutrient Export in Agricultural Watersheds of the United States." *Journal of Environmental Quality* 41(6): 1939–1950.
- Stavins, R.N. 1999. "The Costs of Carbon Sequestration: A Revealed-Preference Approach." *The American Economic Review* 89: 994–1009.
- Taheripour, Farzad, Thomas W. Hertel, and Jing Liu. 2013. "The Role of Irrigation in Determining the Global Land Use Impacts of Biofuels." *Energy, Sustainability and Society* 3(1): 1–18. doi:10.1186/2192-0567-3-4.
- Timmermann, A., 2006. "Forecast Combinations." *Handbook of Economic Forecasting* 1: 135–196.



- Toth, F.L., T. Bruckner, H.M. Füssel, M. Leimbach, and G. Petschel-Held. 2003. "Integrated Assessment of Long-term Climate Policies: Part 1—Model Presentation." *Climatic Change* 56: 37–56.
- Tuppad, P., K.R. Douglas-Mankin, T. Lee, R. Srinivasan and J.G. Arnold. 2011. "Soil and Water Assessment Tool (SWAT) Hydrologic/Water Quality Model: Extended Capability and Wider Adoption." *Transactions of the ASABE* 54(5): 1677–1684. doi: 10.13031/2013.34915.
- Uhlig, Harald. 2005. "What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure." *Journal of Monetary Economics* 52(2): 381–419.
- West, K.D. 1996. "Asymptotic Inference about Predictive Ability." *Econometrica* 64(5): 1067–1084.
- Williams, J.R., J.G. Arnold, J.R. Kiniry, P.W. Gassman, and C.H. Green. 2008. "History of Model Development at Temple, Texas." *Hydrological Sciences Journal* 53(5): 948–960. doi: 10.1623/hysj.53.5.948.
- Wilson, R.S., G. Howard, and E.A. Burnett. 2014. "Improving Nutrient Management Practices in Agriculture: The Role of Risk-based Beliefs in Understanding Farmers' Attitudes toward Taking Additional Action." *Water Resources Research* 50: 6735–6746.
- Wu, J., and K. Segerson. 1995. "On the Use of Aggregate Data to Evaluate Groundwater Protection Policies." *Water Resources Research* 31(7): 1773–1780.
- Wu, J., R.M. Adams, C.L. Kling, and K. Tanaka. 2004. "From Microlevel Decisions to Landscape Changes: An Assessment of Agricultural Conservation Policies." *American Journal of Agricultural Economics* 86(1): 26–41.
- Xabadia, A., R.U. Goetz, and D. Zilberman. 2006. "Control of Accumulating Stock Pollution by Heterogeneous Producers." *Journal of Economic Dynamics and Control* 30: 1105–1130.
- Xabadia, A., R.U. Goetz, and D. Zilberman. 2008. "The Gains from Differentiated Policies to Control Stock Pollution when Producers are Heterogeneous." *American Journal of Agricultural Economics* 90: 1059–1073.
- Zhao, Jinhua. 2015. "Coupled Landscape, Atmosphere, and Socioeconomic Systems (CLASS) in the High Plains Region." Presentation for NSF FEW Workshop, October 2015. Ames, IA.
- Zheng, B., J.B. Campbell, G. Serbin, and J.M. Galbraith. 2014. "Remote Sensing of Crop Residue and Tillage Practices: Present Capabilities and Future Prospects." *Soil and Tillage Research* 138: 26–34.

Zheng, B., J.B. Campbell, Y. Shao, R.H. Wynne. 2013. "Broad-scale Monitoring of Tillage Practices Using Sequential Landsat Imagery." *Soil Science Society of America Journal* 77(5): 1755–1764.