Research Needs for Understanding and Predicting the Behavior of Managed Ecosystems: Lessons from the Study of Agroecosystems

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Abstract

Managed ecosystems are complex, dynamic systems with spatially varying inputs and outputs that are the result of interrelated physical, biological and human decision making processes. We hypothesize that to adequately understand and predict the behavior of these systems, it will be necessary to move beyond stylized theoretical models or loosely coupled disciplinary simulation models to what we describe as fully integrated models. We present a conceptual framework for a more integrated approach to the study of managed ecosystems using the example of agricultural ecosystems. We then propose a science research agenda that fosters coordinated disciplinary research to better understand and quantify linkages across disciplinary models. Key research issues include the effects of spatial scale, the assessment of uncertainty in coupled models, and methods for collecting and analyzing spatially referenced data.

Keywords: managed ecosystems, agroecosystems, economics, prediction, simulation models.

Research Needs for Understanding and Predicting the Behavior of Managed Ecosystems: Lessons from the Study of Agroecosystems

There is a growing recognition by the scientific community that principles from the biological, physical, and social sciences must be integrated to understand and predict the behavior of complex systems such as managed ecosystems. A review of the ecology and economics literatures shows that much of the research on integrating ecology and economics focuses on stylized theoretical models that abstract from empirical details needed to understand and predict behavior of these systems. Empirical research in the field, in contrast, typically involves the linking of detailed disciplinary simulation models, leading to large coupled systems of models that are often used in the style of analysis that has become known as integrated assessment. Typically each model is developed independently from those of the other disciplines, and is designed to operate at temporal and spatial scales most appropriate to individual disciplinary objectives. These distinct disciplinary models can be linked to the degree that it is possible to use outputs of one model as drivers for another.

In this paper, we view managed ecosystems as complex, dynamic systems with spatially varying inputs and outputs that are the result of interrelated physical, biological and human decision making processes. We hypothesize that to adequately understand and predict the behavior of these systems, it will be necessary to move beyond stylized theoretical models or loosely coupled disciplinary simulation models to what we shall describe here as fully integrated models. To achieve this integration, we propose a new comprehensive science research agenda that fosters *coordinated* disciplinary research.

The proposed research is designed to identify and understand relevant processes within models and their fundamental interrelationships so that we may better predict the behavior of complex managed ecosystems. To this end we develop a conceptual framework for an integrated approach to the study of managed ecosystems, and use the example of agricultural ecosystems – arguably the most important and pervasive managed ecosystems – to illustrate our discussion.

While developing our conceptual framework, we summarize some of the important points identified within the literature related to the understanding and prediction of agroecosystem behavior, and offer examples from agroecosystems that illustrate the importance of linking ecology and economics to better understand and predict the behavior of these systems. We discuss some of the problems that are encountered as one moves from a conceptual model to empirical analysis and conclude with recommendations for a science research agenda.

Conceptual Framework for Analysis of Managed Ecosystems

A challenge faced by multi-disciplinary research is to develop a common framework and terminology. Towards that end, we define a *system* as being characterized by a set of interrelated processes, such as crop growth and economic decision-making. *Exogenous driving variables* are determined outside the system and control or limit the flows between the components within the system; *endogenous variables* are determined within the system and include both state and flow variables. *State variables* define the status or performance of the system at specified points in time. Examples of state variables are a farm's economic value defined in dollar units, and an ecosystem's spatial extent defined in hectares. *Flow variables* are inputs into and outputs from processes.

These variables are defined per unit time and depend on process-specific temporal and spatial scales. The magnitude of a state variable is determined by the values of flows up to that point in time. When two or more state variables or flow variables are linked so as to form a loop, a *feedback* occurs between the processes.

Spatial and temporal scales are integral to the definition of processes linking states in a system and to the identification of drivers and states. What is a state variable at one scale can be a driving variable at another scale and vice versa. An example of this is the role that prices play in economic models. At the more aggregate level of a market, economic processes involve many interacting economic agents, and prices are endogenous state variables. At the level of an individual economic agent's decision-making process, prices are exogenous drivers.

We define a *managed system* as one where processes are influenced by purposeful human decision-making. In an agroecosystem, for example, a farmer makes management decisions to accomplish a well-defined purpose, such as to maximize the economic value of the system. We distinguish managed systems from natural systems, where the latter may be affected by human activity that causes changes in the driving variables of the system, but are not purposefully manipulated.

A model of a managed ecosystem, such as an agroecosystem, can be characterized as a set of linked sub-models, each with sets of drivers, state variables, flow variables and processes. This approach of using linked sub-models is often employed in current empirical research on agroecosystems. Figure 1 describes a simplified dryland crop agroecosystem that is composed of a crop ecosystem model and an economic decision model each with a set of drivers and outputs. We describe the modeling system as *loosely* *coupled* when it is constructed using state or flow variables from one sub-model as driving variables in the other sub-model. In Figure 1, the economic decision model determines fertilizer application rates as a function of economic drivers and crop yields. The crop ecosystem model determines yields as a function of exogenous biophysical drivers and fertilizer application rates. Under this structure the two models are loosely coupled by executing each model for a growing season sequentially, passing fertilizer application rates from the economic model to the ecosystem model, and crop yields from the ecosystem model to the economic model.

When states or processes from one sub-model are linked directly to processes in another sub-model, we describe the modeling system as *closely coupled*. Returning to Figure 1, the closely coupled structure is illustrated by the dashed lines linking the fertilizer decisions in the economic model to the crop growth processes in the ecosystem model, and by linking crop growth to the fertilizer decision-making process in the economic model. In the examples discussed below of linking agricultural ecosystem and economic simulation models, the only linkages between models involve land use and crop yields on an annual basis. To operate the crop ecosystem model, representative fertilizer, tillage, and other important management decisions are set as fixed boundary conditions and are not linked to the economic decision model. A more tightly coupled model would make these linkages between biophysical processes and management decision making. In many production systems, multiple fertilizer applications, pesticide applications, and tillage operations are made during the growing season in relation to weather events and crop growth, and these operations can have significant implications for biophysical processes. A good example of the importance of these interactions is provided by recent attention to the potential for agriculture to both emit greenhouse gases and sequester atmospheric CO_2 in the soil. Research shows that these processes could only be represented by a model that captured the interactions between management decisions such as fertilizer use and tillage operations (Robertson and others 2000; Watson and others 2000). Management decisions across seasons, such as crop rotations, interact dynamically with weather events that determine important production constraints such as soil moisture and pest populations. Management decisions are also affected over time by the farmer's acquisition of information about crop and input prices.

Thus, with a closely coupled model it is possible to link processes in ways that more accurately reflect the interactions between biophysical and economic processes. However, with both the loosely and closely coupled models, each disciplinary model has its own set of drivers and only a subset of drivers can be linked from one model component to another. The key point is that the ability to link the disciplinary models is limited by the design of the models.

In contrast to loosely and tightly coupled systems, an *integrated* system would have a single set of drivers and endogenous variables for all disciplinary components. Integration of the agroecosystem in Figure 1 would mean that the same set of biophysical and economic drivers would be inputs into a combined model of crop growth and economic decision making. For example, economic decisions would take account of all relevant information affecting the bio-physical processes of crop growth as well as the exogenous economic drivers; likewise, management decisions such as fertilizer and pesticide applications and tillage operations would be incorporated into the crop growth processes. Thus, the key difference between the loosely or closely coupled systems is that an integrated system operates on temporal and spatial scales dictated by the processes within the model, not by the way that the disciplinary models were designed and coupled.

These considerations lead us to hypothesize that the distinction between loosely coupled, tightly coupled, and integrated modeling systems is fundamental to our ability to understand and predict the behavior of agroecosystems and other managed ecosystems. Integrated systems should predict the behavior of such complex systems better than loosely or tightly coupled systems, particularly in cases where we need to predict beyond the range of observed behavior (such as predicting the effects of unobserved climate change). Yet, there are clearly tradeoffs between model complexity and feasibility. After reviewing the literature on ecosystem and economic models as they relate to predicting the behavior of agroecosystems, we return to this issue of the tradeoffs between model complexity and feasibility in a discussion of a research agenda.

The Agroecosystem Literature

In this section, we selectively review some of the literatures that are relevant to understanding and predicting the behavior of agroecosystems. Our goal is to introduce the reader to the literatures in the field and how they relate to the conceptual framework presented above.

Ecosystem Models. A large number of mathematical models have been developed for agricultural ecosystems, many of which focus on a restricted set of properties and processes, such as crop growth (e.g., Whisler and others 1986; Ritchie 1994), crop-pest interactions (Thomas 1999), hydrologic cycling and transport (e.g., de Willigen and others 1990; Ghadiri and Rose 1992), and soil organic matter and nutrient dynamics (Paustian 1994; Powlson and others 1996). Fewer models exist which employ a ‘wholeecosystem' approach, incorporating all or most of the subsystems involved. Most of these models can be characterized as biogeochemical models that focus on the dynamics of carbon (or biomass) and nutrient elements in the ecosystem (e.g., Hunt and others 1991; Parton and others 1994). Ecosystem processes of primary production, consumption, secondary production, decomposition, and other mass and energy transfers within the system are articulated at various temporal and spatial scales and with varying degrees of mechanistic and empirical formulations.

Common to virtually all such models is the treatment of human influences (i.e., management) as a set of exogenous driving variables or forcing functions, which are conceptually outside the boundaries of the system. An exception to this generalization are models which have been specifically designed for decision-support functions, such as crop and pest management models (e.g., Hodges and others 1998), where development of crop and pest populations dynamically determine management inputs (e.g., pesticide and/or fertilizer application) and the direct response of system variables to those dynamic inputs in a closely coupled fashion. However, such models are highly empirical and are designed specifically for near real time decision-making functions for a narrowly defined system (e.g., a single crop and pest population) and specific spatial and temporal scale (e.g., a single field and growing season). They are not designed to explore broader questions of system properties and complex behaviors, and they do not incorporate economic and ecosystem feedbacks over longer time scales and more extensive spatial scales.

Economic Models. Both mathematical programming models (Adams and others 1995, 1998; Kaiser and others 1993; Kruseman and others 1995; Ruben and others 1998;

Oglethorpe and Sanderson 1999; Prato and others 1996) and econometric production models (Crissman and others 1998; Segerson and Dixon 1998) have been loosely coupled with biophysical models to conduct integrated assessments of agricultural production systems. Econometric models have also been used to explain observed outcomes, such as land use or net returns, as reduced-form functions of economic variables (output and input prices) and biophysical characteristics of land units (Mendelsohn and others 1994; Wu and Segerson 1995; Hardie and Parks 1997). Reduced-form models do not explicitly represent the relationship between productivity and the physical environment, so they cannot be linked to biophysical models to account for phenomena such as CO_2 fertilization in studies of the effects of climate change.

Antle and Capalbo (2001) propose a class of simulation models called econometric-process models. In this approach, conventional econometric production models are used to parameterize a simulation model that represents the structure of agricultural decision making as a sequence of discrete land use decisions and continuous input decisions. By simulating the model with site-specific data and suitable time steps, an econometric process model can be linked to bio-physical process models on a site-specific basis. This class of models can simulate non-linearities and behavior outside the range of observed data better than conventional econometric models.

Bioeconomic and natural resource models. Perhaps the richest areas of research on integrating models are in fisheries, forestry and other renewable resource sectors (Clark 1976; Wilen1985; Brander and Taylor 1998). The major thrust of research in this area has been to develop models for the optimal management of renewable natural resources, and to characterize the dynamic paths of adjustment to steady-state under alternative policy and technology scenarios. This literature has illustrated the importance of population dynamics in determining the optimal levels of resource stocks, and the incorporation of biological resources as a capital stock in the economic analysis. This field of work has often relied on stylized economic and biophysical models that abstract from real-world details for analytical tractability. Sanchirico and Wilen (1999) give some examples of these simplifications to the economic models.

The analysis of renewable resource exploitation has linked economic production models with biological process models in a manner similar to our earlier discussion (Gordon 1954; Smith 1968, 1969). The bioeconomic models have feedbacks between the levels of effort or input use and changes in the size of the resource stock. These linkages have often taken the form of intertemporal feedbacks where the biological growth functions of the natural capital stock are modeled as a constraint on the dynamic economic optimization problem (e.g., Wilen 1985, Capalbo 1986). Bioeconomic models of fisheries (Kellogg and others 1988; Milliman and others 1992; Önal and others 1991; Sylvia and Enriquez 1994; Larkin and Sylvia 1999) and forestry sectors (Bach 1999; Sohngen and others 1999) include biophysical relationships to account for changes in fish or timber stocks over time but do not account for spatial variability or consider issues related to the scale of analysis. More recently, Albers (1996) and Sanchirico and Wilen (1999) have incorporated both intertemporal dynamics and spatial interdependence into conceptual frameworks for optimal management of forest and fishery resources, respectively. However these studies are primarily concerned with examining the equilibrium properties of the models, rather than quantifying the spatial and temporal properties of managed ecosystems. It has been recognized in the bioeconomics literature that there is a need to incorporate features of the systems such as mixed age populations and spatial heterogeneity of biological stocks. Due to the complexity of these systems, this type of analysis requires more reliance on simulation models as a means of understanding and predicting the behavior of these resource systems, similar to what we are suggesting as a path for better understanding managed ecosystems.

A related area of analysis on ecosystem management is found in the ecological economics literature. A recent paper by Barbier (2000) provides a summary of the alternative approaches to treating the environment as an input into production functions, and determining its value through its impact on the productivity of any marketed output. The dynamic approach, which models the effects of a change in an ecosystem input on the growth rate of a resource stock, is most closely related to the discussions of linked and integrated economic-ecosystem models in this paper. Under the dynamic approach the production function-ecosystem link is dynamic where the ecological process or function affects the rate at which a renewable stock increases over time, which in turn impacts the output of the economic production component. Application of this production function approach requires that the relationships between an ecological or environmental regulatory function and the economic activity that it supports are well understood. As Barbier indicates, applications of this approach to cases where there are multiple use systems—where a given ecological function may support multiple economic activities, or may involve more than one ecological input—is more problematic due to the tendency for the production function approach to over estimate the values of the ecological input, or not accurately assess the tradeoffs among alternative ecosystem inputs. However, this research does illustrate the linkages between alternative policies and resulting impacts on the resource stocks, and highlights the values of the ecological functions of many ecosystems in supporting and protecting economic outputs. Barbier indicates that the next phase of the ecological production research is to apply the methods to valuing the many diverse functions of a given ecosystem. To this end, the use of simulation models such as those suggested in this paper may be better suited.

Two other examples of integrated assessments within the ecological area include the work by Montgomery and others (1994) on the spotted owl preservation, and Pfaff and others (2000) on carbon management in tropical forests. In the analysis of spotted owl preservation, the authors assessed the value of the spotted owl to biodiversity using an ecosystem function for this species, imbedded that into the economic production model for wood products, and constructed a marginal cost curve for spotted owl survival. Montgomery and others (1994) employed a spatially-explicit population simulation model to characterize the linkages between changes in demographic and economic parameters and likelihood of species survival. Pfaff and others link a land use decision-making model to an ecosystem model to translate government policies into land-use paths and finally into changes in carbon storage for tropical forests in Costa Rica. Their analysis focuses on the one-directional linkage between economic decision-making and its impact on ecosystem states, similar to the loosely coupled linkages between economic process models and the ecosystem component in Figure 1.

Dynamic Properties of Agricultural Ecosystems. The examples discussed in relation to Figure 1, as well as the examples discussed below, illustrate that the type and strength of feedbacks between ecological and economic processes is central to the understanding of agroecosystem behavior. A feedback is the propagation of the effect of a perturbation through a chain of cause and effect and back to the state variable originally perturbed (Berryman 1989). A positive feedback reinforces the original perturbation, and a negative feedback opposes it. For example (Figure 1), low crop yields accompanied by signs of N limitation (low shoot N concentration) may lead to an economic decision to apply fertilizer, which reduces N limitation and increases crop yield (a negative feedback). Adoption of no-till management by an operator may lead to a decision by local implement dealers to stock specialized equipment for no-till, which may in turn induce more managers to adopt no-till (a positive feedback). In general, positive feedbacks destabilize a system and negative feedbacks tend to stabilize it. However, a negative feedback may destabilize a system if it is expressed via a long chain of cause and effect that introduces a time lag to the system (May 1973). For example, if a decision to fertilize is based on performance of the previous year's crop, instead of the current year's crop, fertilization may be ineffective or even harmful to crop production if precipitation is significantly lower in the current than the previous year. Feedback loops vary in their strength—the degree of reinforcement or opposition of the original perturbation. There is evidence that indirect effects such as feedbacks are vitally important to the stability of systems away from equilibrium (McCann and others 1998), and to the ultimate effects of perturbations in equilibrium systems (Yodzis 1988).

Much theory in ecology has been based on models at steady state (DeAngelis and Waterhouse 1987). Yet there is considerable evidence that many natural ecosystems seldom exist near steady state, except perhaps at large spatial scales (DeAngelis and Waterhouse 1987; Illius and O'Connor 1999). Agricultural ecosystems are unlikely to be at equilibrium because of the long time lag required for soil properties to come into equilibrium with new crops, new management techniques, and altered climate, and due to delays in adoption by operators of new management techniques. The degree of stability observed within the system is likely to vary as a function of the time scale and specific process examined. Thus, analyses of the complexity of agricultural ecosystems must recognize their non-equilibrium nature.

Some nonlinear dynamic systems possess multiple stable steady states (May 1973). A possible example concerns no-till management, which reduces or eliminates cultivation in favor of herbicides for weed control. Once established, no-till management often involves lower costs and equal or higher returns than conventional tillage, yet adoption rates remain low to moderate in many suitable areas. This may in part be due to lower production during an initial transition period following no-till adoption (Dick and others 1998) that persists until the new technology is mastered and soil conditions (i.e., porosity, nutrient cycling) re-equilibrate. This phenomenon might be expressed even in a non-equilibrium system, and economic models should be able to exhibit such behavior.

During the past decade, research has shown that economic data at the market scale may exhibit chaotic properties (Dechert 1996). However, we are not aware of any evidence that coupled agricultural ecosystems or models exhibit chaos. Some research suggests that ecological systems and models commonly do not exhibit chaos (Berryman and Millstein 1989; Ellner and Turchin 1995). However, a few ecological systems appear to be chaotic (Ellner and Turchin 1995) and both ecological and economic models include factors known to promote chaos (Allen 1990): nonlinear effects of state variables on process rates, feedback loops with long time delays (e.g., effects of soil organic matter on primary production, price expectations formed as functions of lagged observed prices), and periodic forcing (weather, cyclic commodity and factor prices, and cyclical macroeconomic phenomena). Thus, it is conceivable that these systems will exhibit chaos under some circumstances.

Chaotic dynamics would have important implications for both management and research. For example, the lack of predictability of chaotic systems would make economic planning difficult if divergence among paths occurs too rapidly. On the other hand, chaos may be a positive feature of some systems (Allen et al. 1993), for example by increasing sensitivity to external controls (Suarez 1999) such as price supports. Economic research on agricultural markets has shown that deterministic market models can exhibit chaotic behavior under conditions typical of such markets such as inelastic demand (Chavas and Holt 1993). However, analysis of chaos in agricultural economic systems thus far has been conducted independently of the ecosystems in which they operate. By integrating ecosystem and economic models, it would be possible to investigate the properties of these systems, taking into account the dynamics and feedbacks both within and between systems. From a management point of view, this type of research could provide greater insight into policy design. For example, this research could provide a better understanding of the limitations of the various types of stabilization policies that have been attempted in the United States and elsewhere since the 1930s, largely without success.

Why Linking Ecology and Economics is Important: Examples from Central U.S. Agroecosystems

In this section we present examples that illustrate why linking and integrating systems is important to understanding and predicting agroecosystem behavior. We also use these examples to identify key research issues. These are summarized in the following sections.

Predicting the Spatial Distribution of Agroecosystem Properties

If we understand the fundamental processes governing an agroecosystem, then we should be able to predict its properties across space and time. But, can we accurately predict agroecosystem behavior using only biophysical processes? If so, then we should be able to predict how the productivity of these systems varies spatially along environmental gradients relying entirely on biophysical models developed to predict crop yields (see the literature discussed above).

Figure 2 shows five-year-average county wheat yields (non-irrigated) across the southern tier of counties in Nebraska. Although precipitation increases nearly two-fold from west to east, wheat yields remain constant or slightly decline, while corn yields generally increase from west to east. Ecological principles alone would predict an increase in wheat production roughly parallel to that of precipitation; it is well established that under water-limiting conditions, primary productivity of native ecosystems in this region is linearly related to plant water availability (Lauenroth and Sala 1992). Indeed, biophysical crop growth models with fixed driving variables (crop management) predict that both wheat and corn yields would increase from west to east along this precipitation gradient. Thus, as one would expect, crop growth processes alone do not provide an accurate prediction of agroecosystem properties across this agroecotone. Instead, it is likely that the observed pattern is strongly influenced by both economic and biophysical factors that influence producer management decisions. For example, in the drier western counties wheat represents the highest value crop for dryland farming and is likely to be grown on the most favorable soils, whereas with higher rainfall in the eastern counties, corn and soybeans have higher value such that wheat may be relegated to lower-quality land. Linking crop models to an economic model of land use and management decisions would provide the means by which the management boundary conditions in the biophysical model could be made to vary in response to climate conditions.

Another example of the importance of integrated modeling for predicting the spatial distribution of agroecosystem properties is motivated by Figures 3 and 4, which show the spatial distribution of agricultural production systems across the central United States. It is unlikely that we could predict agroecosystem behavior—in this case, the spatial distribution of these systems—using only biophysical data such as crop yields. One could hypothesize that the spatial distribution of each system could be explained by the spatial distribution of crop yields. However, the data show that *both* row crop systems and small grain systems are most productive in the Midwest region where soil and climate conditions are highly favorable to the main crops in both systems (Figure 5). Thus, the productivity levels of the two systems do not explain why row crops predominate in the Midwest and small grains predominate in the Great Plains. An economic formulation of the farmer's land use decision problem shows that the choice of system in a given land unit is based on the comparison of the *profitability* of all competing systems at that location. Profitability is a function not only of each system's productivity, but also of prices of crops and costs of production. Our research shows that these prices and costs of production exhibit substantial spatial and temporal variability, and that the spatial distribution of production systems can be explained successfully in terms of productivity and these economic factors affecting the profitability of the competing systems (Antle and others 1999).

Predicting Economic Impacts of Climate Change

Just as biophysical models alone cannot predict the spatial distribution of land use, economic models alone cannot predict the spatial distribution of biophysical change such as climate change. Some economic studies have attempted to quantify the economic impacts of climate change by incorporating climate data directly into reduced-form economic models, thereby allowing the economic adaptation that takes place spatially to be embedded into the reduced form structure. For example, Mendelsohn and others (1994) used a reduced-form econometric approach that incorporates climate data directly into an empirical economic model of land values or net returns. This model was estimated using cross-sectional data, and spatial changes in climate were then used to estimate economic impacts under the assumption that historically observed spatial variation in climate can be used to represent the time-wise effects of future climate change.

A limitation of using reduced-form economic models is that they are not able to incorporate the possible effects of CO_2 fertilization on cropland productivity. Agronomic research shows that there is on average a +30 percent yield response of C_3 crops to doubled CO_2 concentrations (Watson and others 1996, p. 431). Our research into the impacts of climate change in the northern Great Plains shows that without CO_2 fertilization, crop yields could be reduced by up to 50 percent (Antle and others 1999). However, when we use an ecosystem model loosely coupled to an economic land use model we are able to account for the positive effects of CO_2 fertilization that largely offset the negative effects of climate change. Thus, without linkages between the biophysical and economic models, predictions of the economic impacts of climate change are significantly biased.

While this example shows that the linkage of biophysical and economic models offers improved predictive capability over individual disciplinary models, we suspect that more closely coupled models would perform much better under at least some conditions. As we noted earlier, the loosely coupled crop ecosystem and economic models described here do not link fertilization and other management decisions to crop growth, either within or between growing seasons. As the example in Figure 2 demonstrates, economic behavior generally mitigates the effects of biophysical variation, thus incorporating these linkages is likely to significantly improve predictive capability when the magnitude of these interactions is large.

Predicting Biophysical Effects of Climate Change: The Role of Adaptation

Our research on the impacts of climate change in the northern Great Plains also shows the key role that adaptation plays in understanding the biophysical effects of external biophysical drivers such as climate change. If the Century ecosystem model is used to simulate the effects of climate change on carbon levels in agricultural soils, the model indicates that there could be significant losses of soil carbon if land use patterns are assumed to remain fixed. However, when the Century model is coupled with an economic model that predicts land use changes in response to climate change, the analysis shows that land use changes could significantly offset and in some cases reverse the loss of soil carbon predicted by the ecosystem model alone. (Antle and others 1999; Paustian and others 1999).

Effects of Aggregation and Spatial Scale

It is a well-established fact that the statistical properties of spatial data are a function of the choice of spatial scale—for example, as in the "modifiable area unit problem" discussed by Openshaw and Taylor (1979) and Bian (1997) among others. Research on this problem has demonstrated that by changing the scale at which data are gathered, the level of correlation between variables can span values that range from +1 to –1. Thus, the spatial scale chosen for an analysis can significantly affect the information content of data and of models based on those data.

Aggregation of data to different spatial scales also affects the structure and properties of models designed to represent processes. For example, in our research on agroecosystems discussed above, we have shown that economic models of land use decisions at the field scale can account for dynamics of production systems associated with crop rotations. However, when data are aggregated to the county scale, site-specific information about crop rotations is lost, and consequently, models based on aggregate data cannot represent these dynamic aspects of land use. For example, an aggregate model may indicate that the proportion of agricultural land area in certain crops remains relatively constant. This disguises the spatial dynamics of crop production. Although the total area may remain relatively constant those areas electing to move in and out of production of the crop may exhibit significant changes, and these changes have important implications for biophysical processes. For example, it is now known that the frequency of tillage operations has a large effect on soil carbon dynamics, a fact that may be critically important in analysis of how land use and management decisions impact soil carbon sequestration (Paustian and others 1998).

Integration of Biophysical and Economic Models: A Research Agenda

To promote improved understanding of managed ecosystems we believe a future agenda must be designed to promote research on the integration of processes studied by the various disciplines, following the paradigm of Figure 1. This can be accomplished by targeting funding at research that involves close collaboration between scientists from different disciplines. It is important to emphasize, however, that this does not imply a diminution in the importance of individual disciplines. Rather, we see research on the linkage of processes between disciplines as a sub-discipline in its own right. For example, some ecologists may specialize in investigating how ecosystem processes interact with management processes, and likewise some economists may specialize in theory and methods related to managed ecosystems. The existence of such specialists does not mean that the two disciplines should be integrated into one.

In the following sections we identify future research needed to promote better linkages and integration between biophysical, economic, and other social science disciplines using the implications of our conceptual framework and examples.

Research Objectives: Fundamental Mechanisms versus Predictive Efficiency

In defining an agenda for coordinated disciplinary research, it is important for scientists from each discipline to share the same objectives. Our experience with this process suggests that there is often an important difference between disciplines that have typically operated within the logical-deductive, reductionist paradigm and those that operate within a predictive paradigm. On the one hand, research designed to achieve understanding of fundamental processes within the reductionist paradigm is expected to meet the conventional standard of scientific knowledge based on results that can be reproduced with near certainty. This type of research is usually embodied in general, mechanistic relations that are valid across space and time. Here, scientific certainty is viewed as the ultimate goal regardless of cost.

On the other hand, when the goal is to develop the capability to predict behavior, a relative (one might even say, economic) standard becomes relevant: how well one needs to predict behavior depends on the benefits of higher accuracy versus the costs of the information. The structure of a managed ecosystem may in principle be best understood as a set of integrated, mechanistic, biophysical and economic processes. Yet, it may be possible to predict the behavior of a system to an acceptable degree of accuracy using a set of loosely or closely coupled disciplinary models based on both mechanistic and empirical relationships, and using data that are available at a relatively low cost. The use of a more tightly coupled or fully integrated modeling approach might increase prediction accuracy, but this increase in accuracy may come at such a high cost in terms of the data needed to parameterize and run the models that the incremental accuracy would not justify the cost. Indeed, in many applications the data needed to parameterize a highly detailed model at a high spatial resolution may be prohibitively costly.

In our view, both types of research are valid and necessary components of the coordinated disciplinary research agenda we envisage. An important topic for the research agenda is the development of methods to better assess the benefits and costs of alternative modeling approaches.

Aggregation and Spatial Scale

Among the most fundamental problems for the study of managed ecosystems are the effects of aggregation and spatial scale. If it is true that measured properties of processes are site-specific and vary with spatial scale, then how can general properties be established? Likewise, if site-specific data are needed to estimate model parameters, how can predictive models be generalized and used with data that has been aggregated to spatial scales relevant for integrated assessment and management decision-making?

Assessing Uncertainties in Predictive Models

A major methodological challenge is posed by linking various disciplinary models to construct more inclusive models (e.g., the development of integrated assessment models used to examine the potential impacts of climate change). Schneider (1997) argues that the failure to assess effectively the uncertainties and implicit assumptions inherent in models of climate change impacts raises serious questions about their usefulness. A variety of methodological challenges arise in the assessment of uncertainties in large, complex models (Morgan and Henrion 1992). The linkage of two or more models creates additional conceptual and computational difficulties. Nevertheless, these challenges must be addressed—presumably by the use of Monte Carlo methods, sensitivity analysis, and related techniques—if predictive models are to be scientifically credible.

Dynamic Properties of Complex Systems

Another challenge is to investigate the dynamic properties of managed ecosystems such as agroecosystems. Understanding the dynamic properties of these systems is important to both understanding and prediction. Agroecosystems are characterized by properties that can lead to chaotic behavior, for example long feedbacks and cyclical drivers such as prices and climate. Other characteristics, such as capital fixities and indivisibilities, could lead to properties such as multiple stable steady states.

The existence of multiple steady states could have important implications for understanding the behavior of agroecosystems and for the design of public policies intended to increase the long-term productivity and environmental sustainability of the systems.

Data Issues

Most economic and social data are not referenced to a single geographic point, representing instead a region or area. For example, most demographic, agricultural and product price data are reported on the basis of political or other arbitrary geographic regions such as county or state. The spatial variability of, for example, prices influences producer production decisions. This behavior cannot be captured using spatially invariant data. In many cases these areal units do not have ecological coherency.

One reason for the lack of spatially referenced demographic and economic data may be that, until recently, the value of linking site-specific economic behavior to site-specific ecological processes was not well understood. Another reason may be the high cost of collecting disaggregated, site-specific economic data that can be highly temporally variable and thus must be collected with greater frequency (e.g., a soil survey can be conducted once a decade and remain highly accurate, whereas data on agricultural production needs to be collected at least annually). The need for site-specific economic data and its high cost motivate the requirement for methods to determine the necessary elements of minimum data sets and the loss of information associated with data aggregation.

Conclusions

Our conceptual framework for analysis of managed ecosystems suggests a research agenda with objectives aimed at both understanding and prediction. Research to advance fundamental understanding of managed ecosystems should involve coordinated disciplinary research on fundamental processes, their properties, and their integration. Research aiming to advance predictive capability should address the linkage of disciplinary models, and should assess the relative predictive capability of loosely coupled, tightly coupled, and fully integrated models. In addition, this research should address the effects of spatial scale, the assessment of uncertainty in coupled models, and problems associated with collecting and analyzing spatially referenced data.

Research on complex systems is a costly, long-term investment. Both the scientific community and the taxpaying public need to be convinced that this investment is worthwhile. To be judged successful, and to generate continued financial support in an environment in which this research is competing with other important uses of public funds, the proposed research agenda could be successfully implemented in areas where linkage and integration between biophysical, economic, and behavioral sciences is perceived to be highly significant by the scientific community as well as the taxpaying public.

References

Adams RM, Fleming RA, Chang CC, McCarl BA, Rosenzweig C. 1995. A reassessment of the economic effects of global climate change on U.S. agriculture. Climatic Change **30:** 14-167.

Adams RM, McCarl BA, Segerson K, Rosenzweig C, Bryant KJ, Dixon BL, Conner R, Evenson RE, Ojima D. 1998. The economic effects of climate change on U.S. agriculture. Chapter 2 in Mendelsohn R, Neumann JE, editors. The economics of climate change. Cambridge: Cambridge University Press.

Albers H. 1996. Modelling ecological constraints on tropical forest management: spatial interdependence, irreversibility, and uncertainty. Journal of Environmental Economics and Management **30:** (1) 73-95.

Allen JC. 1990. Factors contributing to chaos in population feedback systems. Ecological Modelling **51:** 281-298.

Allen JC, Schaffer WM, Rosko D. 1993. Chaos reduces species extinction by amplifying local population noise. Nature **364:** 229-232.

Antle JM, Capalbo SM, Hewitt J. 1999. Testing hypotheses in integrated impact assessments: climate variability and economic adaptation in Great Plains agriculture. 1998/99 Annual Report. National Institute for Global Environmental Change. http://nigec.ucdavis.edu.

Antle JM, Capalbo SM. 2001. Econometric-process models for integrated assessment of agricultural production systems. American Journal of Agricultural Economics, in press.

Bach CF. 1999. Economic incentives for sustainable management: a small optimal control model for tropical forestry. Ecological Economics **30:** 251-265.

Barbier EB. 2000. Valuing the environment as input: review of applications to mangrove-fishery linkages. Ecological Economics **35:** 47-61.

Berryman AA. 1989. The conceptual foundations of ecological dynamics. Bulletin of the Ecological Society of America **70:** 230-236.

Berryman AA, Millstein JA. 1989. Are ecological systems chaotic – and if not, why not? Trends in Ecology and Evolution **4:** 26-28.

Bian L. 1997. Multiscale nature of spatial data in scaling up environmental models. Quattrochi DA, Goodchild MF, editors. Scale in remote sensing and GIS. New York: Lewis Publishers.

Brander JA, Taylor MS. 1998. The simple economics of Easter Island: a Ricardo-Malthus model of renewable resource use. American Economic Review **88:** (1) 119-138.

Capalbo SM. 1986. Temporary equilibrium production models for a common-property renewable resource sector. Journal of Econometrics 33: 263-284.

Chavas JP, Holt MT. 1993. Market instability and nonlinear dynamics. American Journal of Agricultural Economics **75:** 113-120.

Clark C. 1976. Mathematical bioeconomics: the optimal management of renewable resources. New York: John Wiley and Sons.

Crissman CC, Antle JM, Capalbo SM, editors. 1998. Economic, environment, and health tradeoffs in agriculture: pesticides and the sustainability of Andean potato production. Boston: Kluwer Academic Publishers.

DeAngelis DL, Waterhouse JC. 1987. Equilibrium and nonequilibrium concepts in ecological models. Ecological Monographs **57:** 1-21.

Dechert WD, editor. 1996. Chaos theory in economics: methods, models and evidence. Cheltenham, UK: Edward Elgar Publishing.

de Willigen P, Bergstrom L, Gerritse RG. 1990. Leaching models of the unsaturated zone, their potential use for management and planning. Decoursey DG, editor. Proceedings of the international symposium on water quality modelling of agricultural non-point sources. Washington, DC: U.S. Department of Agriculture. p105-128

Dick WA, Blevins RL, Frye WW, Peters SE, Christenson DR, Pierce FJ, Vitosh ML. 1998. Impacts of agricultural management practices on C sequestration in forest-derived soils of the eastern corn belt. Soil Tillage Research **47:** 235-244.

Ellner S, Turchin P. 1995. Chaos in a noisy world: new methods and evidence from time-series analysis. American Naturalist **145:** 343-375.

Ghadiri H, Rose CW, editors. 1992. Modelling chemical transport in soils. Boca Raton (FL): Lewis Publishers.

Gordon HS. 1954. The economic theory of a common-property resource: the fishery. Journal of Political Economy **62:** 124-142.

Hardie IW, Parks PJ. 1997. Land use with heterogeneous land quality: an application of an area base model. American Journal of Agricultural Economics **79:** 299-310.

Hodges HF, Whisler FD, Bridges SM, Reddy KR, McKinion JM. 1998. Simulation in crop management: GOSSYM/COMAX. Peart RM, Curry RB, editors.

Agricultural systems modeling and simulation. New York: Marcel Dekker, Inc. p235-281

Hunt HW, Trlica MJ, Redente EF, Moore JC, Detling JK, Kittel TGF, Walter DE, Fowler MC, Klein DA, Elliott ET. 1991. Simulation model for the effects of climate change on temperate grassland ecosystems. Ecological Modelling **53:** 205-246.

Illius AW, O'Connor TG. 1999. On the relevance of nonequilibrium concepts to arid and semiarid grazing systems. Ecological Applications **9:** 798-813.

Kaiser HM, Riha SJ, Wilks DS, Rossiter DG, Sampath R. 1993. A farm-level analysis of economic and agronomic impacts of gradual climate warming. American Journal of Agricultural Economics **75:** 387-398.

Kruseman G, Ruben R, Hengsdijk H, van Ittersum MK. 1995. Farm household modelling for estimating the effectiveness of price instruments in land use policy. Netherlands Journal of Agricultural Science **43:** 111-123.

Kellogg RL, Easley, Jr. JE, Johnson T. 1988. Optimal timing of harvest for the North Carolina bay scallop fishery. American Journal of Agricultural Economics **70:** (1) 50-61.

Larkin SL, Sylvia G. 1999. Intrinsic fish characteristics and intraseason production efficiency: a management-level bioeconomic analysis of a commercial fishery. American Journal of Agricultural Economics **81:** 29-43.

Lauenroth WK, Sala OE. 1992. Long-term forage production of North American shortgrass steppe. Ecological Applications **2:** 397-403.

May RM. 1973. Stability and complexity in model ecosystems. Princeton (NJ): Princeton University Press.

McCann K, Hastings A, Huxel GR. 1998. Weak interactions and the balance of nature. Nature **395:** 794-798.

Mendelsohn R, Nordhaus WD, Shaw D. 1994. The impact of global warming on agriculture: a Ricardian analysis. American Economic Review **84:** 753-771.

Milliman SR, Johnson BL, Bishop RC, Boyle KJ. 1992. The bioeconomics of resource rehabilitation: a commercial-sport analysis for a Great Lakes fishery. Land Economics **68:** 191-210.

Montgomery CA, Brown Jr GM, Adams DM. 1994. The marginal cost of species preservation: the northern spotted owl. Journal of Environmental Economics and Management **26**: 111-128.

Morgan MG, Henrion M. 1992. Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge: Cambridge University Press.

Oglethorpe DR, Sanderson RA. 1999. An ecological-economic model for agri-environmental policy analysis. Ecological Economics **28:** 245-266.

Openshaw S, Taylor PJ. 1979. A million or so correlation coefficients: three experiments on the modifiable areal unit problem. Wrigley N, editor. Statistical applications in the spatial science. London: Pion Limited.

Önal H, McCarl BA, Griffin WL, Matlock G, Clark J. 1991. A bio-economic analysis of the Texas shrimp fishery and its optimal management. American Journal of Agricultural Economics **73:** 1161-1170.

Parton WJ, Ojima DS, Cole CV, Schimel DS. 1994. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. Bryant RB, Arnold RW, editors. Quantitative modelling of soil forming processes. SSSA

Special Publication 39. Madison (WI): Soil Science Society of America, p147-167.

Paustian K. 1994. Modelling soil biology and biogeochemical processes for sustainable agriculture research. Pankhurst C, Doube BM, Gupta VVSR, Grace PR, editors. Management of soil biota in sustainable farming systems. Melbourne: CSIRO Publishing. p182-196.

Paustian K, Cole CV, Sauerbeck D, Sampson N. 1998. CO_2 mitigation by agriculture: an overview. Climatic Change **40:** 135-162.

Paustian K, Elliott ET, Hahn L. 1999. Agroecosystem boundaries and C dynamics with global change in the central United States. FY 1998/1999 Progress Report, National Institute for Global Environmental Change. http://nigec.ucdavis.edu.

Pfaff ASP, Kerr S, Hughes RF, Liu S, Sanchez-Azofeife GA, Schimel D, Tosi J, Watson V. 2000. The Kyoto protocol and payments for tropical forest: an interdisciplinary method for estimating carbon-offset supply and increasing the feasibility of a carbon market under the CDM. Ecological Economics **35:** 203-221.

Powlson DS, Smith P, Smith JU, editors. 1996. Evaluation of soil organic matter models. NATO ASI Series I, Vol 38, Heidelberg: Springer-Verlag.

Prato T, Fulcher C, Wu S, Ma J. 1996. Multiple-objective decision making for agroecosystem management. Agricultural and Resource Economics Review **25:** 200-212.

Ritchie JT. 1994. Classification of crop simulation models. Uhlir PF, Carter GC, editors. Crop modelling and related environmental data, a focus on applications for arid and semiarid regions in developing countries. Monograph Series, Vol 1. Paris: CODATA Commission on Global Change. p3-14.

Robertson GP, Paul EA, Harwood RR. 2000. Greenhouse gases in intensive agriculture: contributions of individual gases to the radiative forcing of the atmosphere. Science **289** (September): 1922–1924.

Ruben R, Moll H, Kuyvenhoven A. 1998. Integrating agricultural research and policy analysis: analytical framework and policy applications for bio-economic modelling. Agricultural Systems **58:** (3) 331-349.

Sanchirico JN, Wilen JE. 1999. Bioeconomics of spatial exploitation in a patchy environment. Journal of Environmental Economics and Management **37:** 129-150.

Schneider SH. 1997. Integrated assessment modeling of global climate change: transparent rational tool for policy making or opaque screen hiding value laden assumptions? Environmental Modeling and Assessment **2:** (4) 229-248.

Segerson K, Dixon BL. 1998. Climate change and agriculture: the role of farmer adaptation. Chapter 4 in Mendelsohn R, Neumann JE, editors. The impact of climate change on the U.S. economy. Cambridge: Cambridge University Press.

Smith VL. 1968. Economics of production from natural resources. American Economic Review **58:** 409-431.

Smith VL. 1969. On models of commercial fishing. Journal of Political Economy **77:** 181-198.

Sohngen B, Mendelsohn R, Sedjo R. 1999. Forest management, conservation and global timber markets. American Journal of Agricultural Economics **81:** (1) 1-13.

Sylvia G, Enriquez RR. 1994. Multiobjective bio-economic analysis: an application to the Pacific whiting fishery. Marine Resource Economics **9:** 311-328.

Suarez I. 1999. Mastering chaos in ecology. Ecological Modelling **117:** 305-314.

Thomas MB. 1999. Ecological approaches and the development of "truly integrated" pest management. Proceedings of the National Academy of Sciences **96:** 5944-5951.

Watson RT, Zinyowera MC, Moss RM. 1996. Climate change 1995: impacts, adaptations and mitigation of climate change: scientific-technical analyses. Cambridge: Cambridge University Press.

Watson RT, Noble IR, Bolin B, Ravindranath NH, Verardo DJ, Dokken DJ, editors. 2000. Land use, land-use change, and forestry. A special report of the IPCC, Cambridge, England: Cambridge University Press.

Whisler FD, Acock B, Baker DN, Fye RE, Hodges HF, Lambert JR, Lemmon HE, McKinion JM, Reddy VR. 1986. Crop simulation models in agronomic systems. Advances in Agronomy **40:** 141-208.

Wilen JA. 1985. Bioeconomics of renewable resource use. Chapter 2 in Kneese AV, Sweeney JL, editors. Handbook of natural resource and energy economics. Volume 1. Amsterdam: North-Holland Publishers.

Wu J, Segerson K. 1995. The impact of policies and land characteristics on potential groundwater pollution in Wisconsin. American Journal of Agricultural Economics **77:** (November) 1033-1047.

Yodzis P. 1988. The indeterminancy of ecological interactions as perceived through perturbation experiments. Ecology **69:** 508-515.

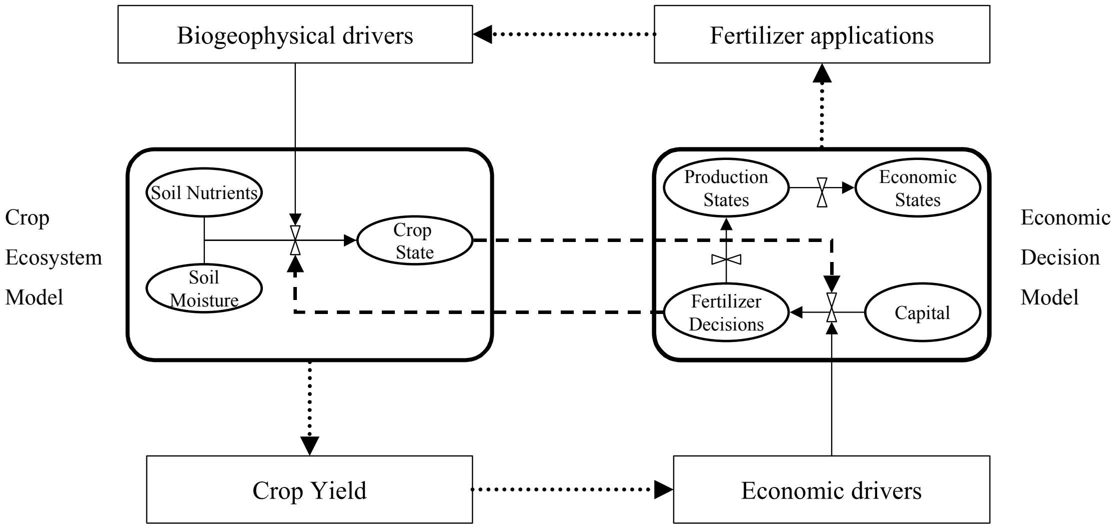


Figure 1. Agroecosystems Represented as Loosely or Closely Coupled Ecosystem and Economic Models. Dotted connectors represent feedbacks from system states to drivers in a loosely coupled model, dashed connectors represent feedbacks between processes in a closely coupled agroecosystem model.

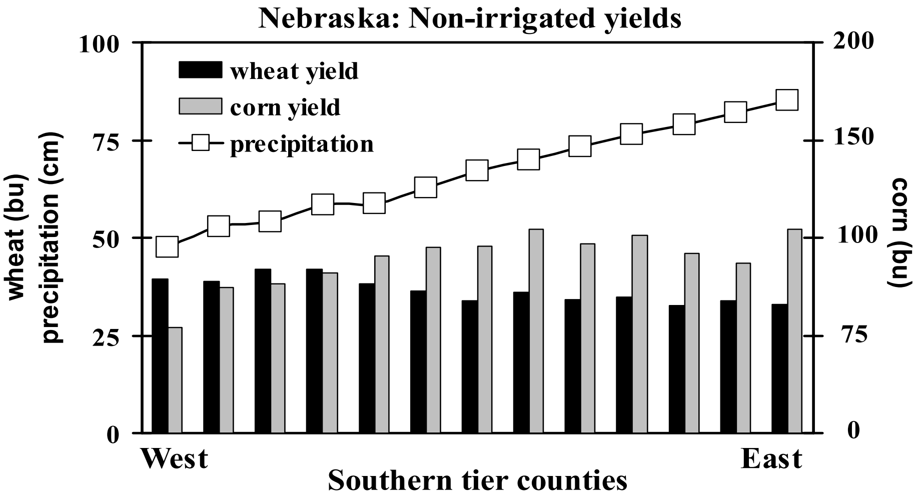


Figure 2. Wheat, Corn Yields (bu/ac), and Precipitation Gradient in Southern Nebraska

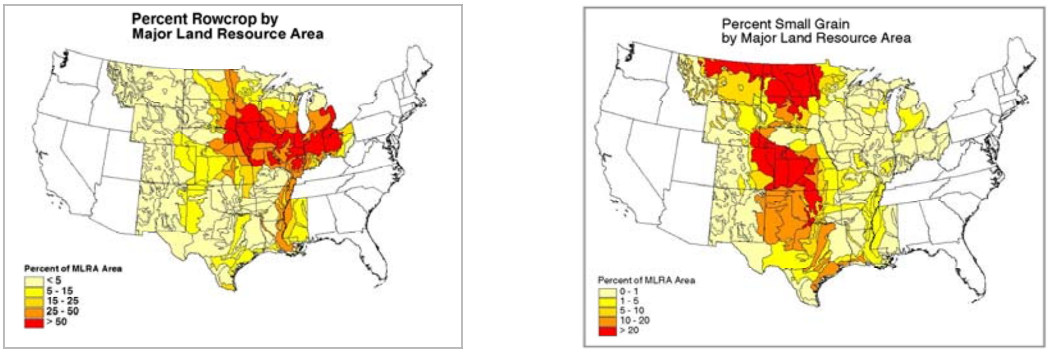
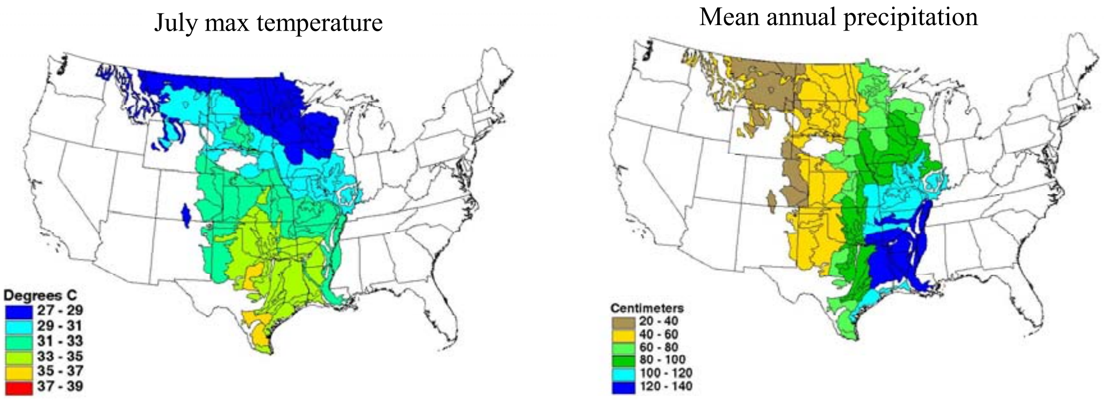


Figure 3. Spatial Distribution of Rowcrop and Small Grain Agroecosystems in the Central United States by Major Land Resource Area


July max temperature

Mean annual precipitation

Figure 4. Temperature and Precipitation Patterns by Major Land Resource Area in the Central United States

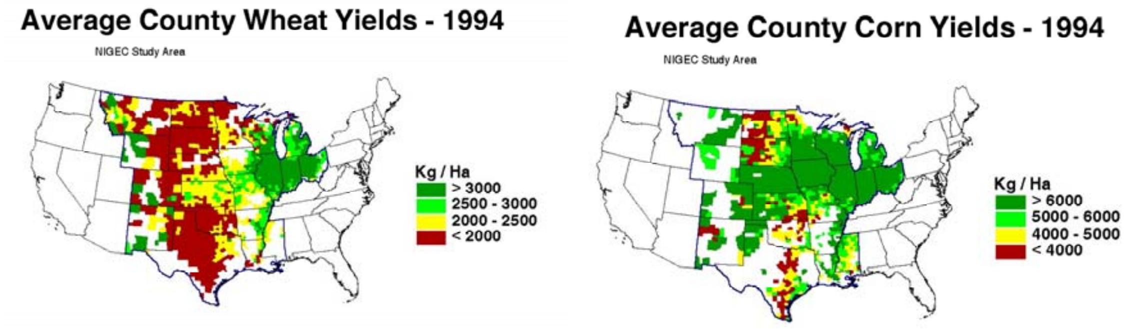


Figure 5. Spatial Distribution of Wheat and Corn Yields in the Central United States, 1994

Figure Legends

Figure 1. Agroecosystems Represented as Loosely or Closely Coupled Ecosystem and Economic Models

Figure 2. Wheat, Corn Yields (bu/ac), and Precipitation Gradient in Southern Nebraska

Figure 3. Spatial Distribution of Rowcrop and Small Grain Agroecosystems in the Central United States by Major Land Resource Area

Figure 4. Temperature and Precipitation Patterns by Major Land Resource Area in the Central United States

Figure 5. Spatial Distribution of Wheat and Corn Yields in the Central United States, 1994