Abstract. This paper reviews land use modeling approaches for assessing the economic and environmental impacts of agricultural intensification. It discusses the theoretical foundations of the modeling approaches, describes how to parameterize such models when micro-level data are available, and examines how to integrate them with biophysical models for policy evaluation. Based on the literature review, the paper identifies key research questions and discusses appropriate methods and data and promising research areas for investigating those questions.
1. Introduction

Agriculture around the world will face tremendous pressure for intensification over the next 50 years. The United Nations forecasts the world population will increase by one third from 2013–2050. This will dramatically increase the demand for food. The economic transformation currently under way in China, India and other developing nations also has profound implications for global resource demand and environmental conditions. As these countries shift from largely agrarian to industrial economies, their demand for food, energy and natural resources will increase with rising income. Agriculture is expected to meet growing demands for food and fiber. At the same time, agriculture is also expected to provide increased animal welfare and more ecosystem services and play a major role in producing renewable energy, including bioenergy. These new demands will intensify competition for land around the world and will put the role of agricultural intensification at the center stage.

Agricultural intensification is a production system conventionally characterized by a low fallow ratio and an intensive use of inputs, such as capital, labor, pesticides, and chemical fertilizers, to raise agricultural yields, thereby increasing farmers’ income and reducing poverty. It remains a question, however, whether such intensification can harmonize food production and environmental protection. Previous studies demonstrated that intensive agricultural production has led to increased erosion, lower soil fertility, and reduced biodiversity (Matson et al. 1997). Intensification may cause conversions of marginal lands, such as grasslands or rangeland, to crop production, leading to land degradation (Li et al., 2013). Intensification may also have negative regional externalities because water use and chemical runoff can impact areas beyond those actually cultivated (Matson et al. 1997; Tilman et al. 2002).
In response to the global pressure for balancing economic development and environmental protection, the IFPRI-led BioSight project was established. This project aims to provide a novel and integrated approach to strategic policy analysis for sustainable agricultural intensification at the intersection of food, water, land, energy, and the environment. Sustainable agricultural intensification is generally defined as a process whereby agricultural yields are increased without generating adverse environmental impacts. Sustainable agricultural intensification includes a range of farming practices, from specific agro-ecological methods, to practices used in commercial agriculture, to biotechnology. This concept has received increased attentions in some high-level political and scientific circles in recent years because it offers a potentially practical pathway towards the goal of producing more food with less impact on environment. BioSight aims to advance the science of integrated bioeconomic modeling by developing a set of tools and data with strong micro-level and spatially-explicit grounding to (1) improve calibration of existing models, (2) extend their analysis to address alternative policies for scaling up of sustainable intensification, and (3) generate actionable policy recommendations on sustainable intensification that are appropriate to short- and medium-term outlooks.

To support BioSight’s development of models, tools, and problem-focused analytics, this report reviews land-use modeling approaches for assessing the environmental and ecological impacts of agricultural intensification. The goal of this paper is to lay a solid foundation for the development of models, tools, and problem-focused analytics that explore the impacts and implications of agricultural intensification. The specific objectives are:

1. Conduct a thorough literature review on land use modeling approaches for assessing the economic and environmental impacts of agricultural intensification, and describe how best to parameterize such models, especially those dealing with the data-rich environment, e.g.,
when micro-level household surveys are available, or when detailed spatial data of land use and land cover exist.

2. Review the methods for integrating land use models and biophysical models to assess the impact of land use change on ecosystem services, and based on the literature review, and identify important methodological/data gaps in the literature.

3. Identify 3–5 top research questions relating to land use change and sustainable intensification that have important policy implications and scientific significance, and discuss the appropriate methods and data for investigating these research questions.

4. Propose a set of promising study areas in which these questions could be explored and provide guidance as to the minimum data requirements.

In this paper, land use change refers to more than simply the pattern of different land covers (e.g., cropland, grassland, rangeland) in space. Rather, it includes any changes in arrangements, activities, and inputs that people undertake in a certain land cover type. In this sense, agricultural intensification is a major cause of land use change. Agricultural intensification can occur at both the intensive margin and the extensive margin. Agricultural intensification occurs at the intensive margin when more input is used for a given land area (e.g., more fertilizer application per acre in the production of corn). Agricultural intensification occurs at the extensive margin when a less input-intensive land use is converted to a more input-intensive land use (e.g., conversions of grassland to crop production).

Section 2 discusses the theoretical foundations of the modeling approaches and describes how to parameterize such models when aggregate or micro-level data are available. Section 3 discusses the environmental/ecological impacts of agricultural intensification and land use change and examines how to integrate economic and biophysical models to assess the impacts.
Based on the literature review, section 4 identifies important research questions that have important policy implications and scientific significance, and reviews the appropriate methodology and data for investigating these research questions. Section 5 concludes with a brief discussion of promising study areas.

2. Theories and Econometric Approaches for Modeling Land Use

Economic studies of land use and land use change can be arrayed in a number of dimensions: theoretical versus empirical; structural versus reduced form; econometric versus other empirical approaches; farm, regional, national, versus international-level studies; disaggregate versus aggregate; extensive-margin versus intensive-margin studies; drivers versus consequences-orientated studies, policy versus methods-orientated studies (see Table 1). The first three dimensions are related to the study method, the next three to the study scope, and the last two to the study objective. For example, Irwin and Wrenn (forthcoming) provide an overview and assessment of the main methods used to model land use change and classify land use models along two dimensions: first, models that are structural versus reduced form and second, econometric models versus other empirical approaches that are used to specify parameter values.

Duke and Wu (forthcoming) arrange the chapters in the Oxford Handbook of Land Economics in several dimensions. They divide the chapters into four main sections focusing on drivers of land use change, consequences of land use change, methodological developments, and the economics of land use law and policy, respectively. The methodological section includes chapters that focus on econometric, simulation, and experimental methods, respectively.
Table 1. Dimensions for Arraying Land-Use Studies

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<th>Dimensions</th>
<th>Examples</th>
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<td>Theoretical vs. empirical</td>
<td>Capozza and Helsley (1989) vs. Li et al. (2013)</td>
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To a large extent, the scope and method of empirical studies are driven by the available data. Applied economists must wrestle with the tradeoff between a theoretically consistent model specification and tractability constraints imposed by data (Wu and Adams, 2002). With this in mind and considering the goal of the *BioSight* project, we discuss the different theories and empirical approaches for modeling land use when different levels of data are available in this section.
2.1 Modeling land use with micro-level data

When household-level survey data are available, the microparameter distribution model can serve as a conceptual framework for modeling land allocation decisions (We and Segerson, 1995). Specifically, consider a farm that has $N_j$ acres of land of type $j$ ($j = 1 \ldots, J$). Land types can be distinguished by land characteristics such as soil type, slope and permeability. The total acreage for the farm is then $N = N_1 + N_2 + \ldots + N_j$. For each land type, the farmer must decide how to allocate the $N_j$ acres across crops. Let $i = 1, \ldots, I$ index crops and let $m = 1, \ldots, M$ index variable inputs (including pesticides and fertilizers). The farmer faces exogenous crop prices $p = (p_i, \ldots, p_I)$ and exogenous input prices $w = (w_1, \ldots, w_M)$, and chooses the amount of land type $j$ to produce crop $i$, $n_{ij}$. Let $p_{ij}(p_i, w, n_{ij})$ denote the restricted profit function for crop $i$ grown on land type $j$, given $n_{ij}$. For each land type, the farmer then chooses the land allocation that maximizes total profit:

\[
\text{Max}_{(n_{ij}, \ldots, n_{ij})} \quad \sum_{i=1}^{I} p_{ij}(p_i, w, n_{ij})
\]

subject to

\[
N_{1j} + N_{2j} + \ldots + N_{ij} = N_j.
\]

The solution to this problem gives the optimal land allocation for type $j$ land:

\[
n_{ij}^* = n_{ij}(p, w, N_j).
\]

Assume this function is homogeneous of degree 1 in $N_j$. Then

\[
n_{ij}^* = n_{ij}(p, w, 1)N_j.
\]

The total acreage devoted to production of crop $i$ is then given by:

\[
n_i^* = \sum_{j=1}^{J} n_{ij}^*(p_i, w, 1)N_j.
\]

Equation (3) can be written in share form as
Note that the shares depend on all output and input prices, and on the entire distribution of land characteristics for the farm.

There are two approaches to the estimation of the share equations in equation (4) (Wu and Segerson, 1995). The first is to specify a flexible functional form, such as translog or normalized quadratic, for the restricted profit function and then derive the implied functional form for the share equations. This is the approach taken by Moore and Negri (1992) as well as by others who have studied multi-product acreage or supply decisions (e.g., Weaver, 1983; Shumway, 1983). Alternatively, one can assume a flexible functional form for the share equations themselves. For example, the share equations can be assumed to take the logistic form, as in Considine and Mount; Chavas and Segerson (1986); Wu and Segerson (1995), Wu and Tanaka (2005). The first approach has the advantage of providing a theoretical link between the forms of the profit function and the share equations. However, the desirable local properties do not necessarily hold globally (Wales, 1977). In addition, it does not ensure that predicted shares lie in the zero-one interval. In contrast, use of the logistic form ensures that the shares will lie between zero and one. The logit model has also been shown to outperform other flexible functional forms, such as the Almost Ideal Demand System and the translog (Lutton and LeBlanc, 1984; Rothman, Hong, and Mount, 1993) and has been widely used in economic analysis, including the study of farmers’ land allocation decisions (Lichtenberg, 1989; Wu and Segerson, 1995; Hardie and Parks, 1997; Plantinga, Mauldin, and Miller, 1999), the choice of irrigation technologies (Caswell and Zilberman, 1985), and the choice of alternative crop management practices (Wu and Babcock, 1998).
Micro-level data may also exist for a selected sample of individual parcels. For example, the U.S. Natural Resource Inventory (NRI) is conducted every five years to determine the status, condition, and trend in the nation’s soil, water, and other related resources. It contains land use and conservation practices information at more than 800,000 sites (fields) across the continental United States. In this case, the random utility model can serve as a theoretical foundation for modeling land use choices at individual parcels. Specifically, let \( u_i(X_{ij}) \) be the farmer’s utility from growing crop \( i \) on parcel \( j \). Because the farmer’s preferences are unknown to the researcher, \( u_i(X_{ij}) \) can be considered a random variable and be written as

\[
(5) \quad u_i(X_{ij}) = v_{ij}(X_{ij}) + \epsilon_{ij}, \quad i = 1, 2, ..., N, j=o,c.
\]

where \( v_{ij}(X_{ij}) \) is the mean of \( u_i(X_{ij}) \) and is specified as \( v_{ij}(X_{ij}) = X_{ij}b_i \), and \( \epsilon_{ij} \) is a random error term. If the residuals \( \epsilon_{ij} \) are assumed to be independently and identically distributed with the extreme value distribution, then the probability that the farmer will choose crop \( i \) on parcel \( j \) is given by a multinomial logit model (Maddala, p. 60):

\[
(6) \quad P_{ij} = \frac{e^{X_{ij}b_i}}{\sum_{k=1}^{I} e^{X_{ij}b_k}}, \quad i = 1, ..., I.
\]

The marginal effects of changes in explanatory variables on crop choices in a logit model are nonlinear combinations of the explanatory variables and can be written as

\[
(7) \quad \frac{\partial P_{ij}}{\partial X_{ij}} = P_{ij} \left( \sum_{k=1}^{I} P_{kj} \sum_{l} b_l \right).
\]

The sign and magnitude of this marginal effect have no direct relationship with any specific coefficient.
2.2 Modeling land use with aggregate data

When micro-level data are unavailable, relationships representing the behavior of individual economic agents are frequently estimated using aggregate or “macro” data (Grunfeld and Griliches, 1960). These empirical macro relationships are then used for making inferences about individual behavior and/or for making aggregate predictions. Two potential problems may arise from this practice (Wu and Adams, 2002). One, which is often referred to as the aggregation problem, concerns the connections between micro and macro behavior (Chambers and Pope, 1991). If aggregate relationships are used to make inferences about individual behavior, one must consider the conditions under which the distribution of individual characteristics can be ignored so that the results can be treated as if they are the outcome of the decision of a single “representative” firm or consumer. If these conditions are met, the relationships derived from micro theory can be estimated with aggregate data and behavioral interpretations can be made from the estimated parameters.

The second problem concerns the relative accuracy of predictions made by micro and macro models. With the advance of data collection and management technologies such as Geographic Information Systems (GIS) and satellite images, more and more micro-level, spatially articulated data are becoming available. With these data, it is increasingly possible to estimate micro models and then statistically aggregate the micro-level predictions to the aggregate level by using the distribution of individual characteristics. The question is whether the micro approach, facilitated by the availability of micro data, will provide better predictions of aggregate outcomes than traditional aggregate models.

A large body of literature has focused on the aggregation problem in general and two lines of inquiry in particular (Wu and Adams, 2002). The first seeks the requisite conditions on
micro behavior for a representative producer or consumer to exist (Gorman (1953); Muellbauer (1975); Klein (1946); Theil (1971); Hildenbrand (1983); Chiappori (1985); Stoker (1984); Blackorby and Schworm (1988)). These conditions are often found to be quite stringent. The second line of inquiry has focused on the problem of ‘aggregation bias,’ defined by the derivation of the macro parameters from the average of the corresponding micro parameters (e.g., Theil, 1971; Gupta, 1971; Sasaki, 1978; Lee et al., 1989; Shumway, 1995; Love, 1999).

In contrast to the aggregation problem, the issue of prediction accuracy has received less attention. In a seminal paper, Grunfeld and Griliches (GG) (1960) examined the relative power of micro and macro models for explaining the variability of the aggregate dependent variable and found that the aggregate equation may explain the aggregate data better than a combination of micro equations. Sasaki (1978) reexamined the issue using data from four Japanese industries and found that the explanatory power of the macro models is not necessarily higher than that of micro models. Pesaran et al. (1989) developed a more general criterion for choosing between micro and macro models and applied it to labor demand in UK industries. They found that for the manufacturing industries the prediction criterion marginally favors the aggregate model but over all industries the disaggregate models are strongly preferred. Wu and Adams (2002) examined the issue in the context of predicting land allocation. They show that even in the context of linear prediction models the issue of whether one should choose micro or macro models to make aggregate predictions cannot be generally resolved by a priori reasoning.

Because of a lack of disaggregate data, most acreage response models are estimated using regional or national data (e.g., Houck and Ryan, 1972; Lidman and Bawden, 1974; Chavas and Holt, 1990; Chavas, Pope, and Kao, 1983). For example, Lichtenberg (1989) estimated a county-level acreage response model to examine the interaction between land quality, cropping patterns,
and irrigation development. Wu and Segerson (1995) estimated a similar model to examine the effect of government commodity programs and land characteristics on groundwater pollution in Wisconsin. Hardie and Parks (1997) used county level data to analyze the impact of land quality on land allocation between agriculture and forests. In these county-level analyses, $P_{ijt}$ is estimated as the share of potential cropland allocated to crop $i$ in county $j$ in year $t$, and the beta parameters are estimated using the following logistic regression equations, which are derived by taking the log of the ratio of $P_{ijt}$ and $P_{ijt}$ in (6):

\[
\ln \left( \frac{P_{ijt}}{P_{ijt}} \right) = \beta x_{ijt} + \epsilon_{ijt}, \quad i = 1, \ldots, (I-1)
\]

where $\beta$ is normalized to zero to reduce the indeterminacy in the model (Greene, 1990, p. 697).

Because county size, cultivation history, and other disturbance factors differ across counties, heteroskedasticity may exist in the county-level model. Heteroskedasticity can be tested using the Lagrange multiplier test (Greene, 1990, 1990, p. 467). Also, because the disturbances affecting one crop in one year may affect the same crop in other years, autocorrelation was tested using the Durbin test. In addition, with land allocation imposing joint production decisions and disturbances for different crops reflecting common factors (e.g., climate and the general state of the economy), contemporaneous correlation (i.e., correlation between error terms for different crops) may be present. Wu and Brorsen (1995) discuss tests for detecting these econometric problems and propose an empirical procedure that can be used to address all of these econometric problems at the same time. Finally, because the disturbances affecting one county may also affect the neighboring counties, spatial autocorrelations may exist.
It is very challenging to correct the spatial autocorrelation in the logistic model. Li et al. (2013) proposes an approach to address this problem in a recent study.

3. Modeling the Environmental/Ecological Impacts of Land Use

So far we have focused on the theory and methods for analyzing the drivers of land use change. But land use change can have wide-ranging environmental/ecological consequences. When wetlands are drained for crop production, it will affect the probability of flooding lower in the watershed, the flow of nutrients through ecosystems and water quality in adjoining areas. When natural habitats are modified to serve human uses, valuable ecosystem services may be altered or destroyed. With the increase in human population and scope of economic activity, there are growing concerns about the impact of human actions on natural systems.

Natural systems provide a broad range of ecosystem services upon which humans and all other species depend. The list of important ecosystem services includes: water purification; flood control and soil retention; nutrient cycling; generation and renewal of soil and soil productivity; crop pollination; pest control; maintenance of species and genetic information; composition of the atmosphere and climate stabilization. Land use change not only affects the provision of these vital ecosystem services, but is also affected by them. Although it may be true that individual land management decisions do not threaten the life support in total, their cumulative impact may cause important local changes to ecosystems and contribute to changes in larger-scale processes such as global climate change. Figure 1 below illustrates the interactions between human and ecological systems through land use change. Table A1 in the Appendix provides a comprehensive list of references on the effect of land use and land use change on selected watershed health indicators.
In this section, we first review and assess the economic literature that examines how land change affects provision of several specific ecosystem services. We then discuss how economic and biophysical models could be integrated for policy analysis evaluation.

3.1 Land use and water quality and quantity

It is now well established that economic activities can cause water pollution and that agricultural land uses in particular are a source of many contaminants. The environmental impacts of land use change depends on land characteristics, such as soil type, depth to groundwater, and the
underlying geological structure of the land. Since land uses respond to government policies, those policies can also play an important role in determining the level of water quality.

Much research has focused on the effect of land use on water quality. These studies can be categorized based on the types of land use they analyze. For example, there is a large body of literature on the effect of agricultural land use (cropping patterns and farming practices) on water quality. There are also studies that focus on the effect of forestland or wetland on water quality or compare their effects with agricultural and other land uses. Studies in each category can be further divided into subcategories. For example, studies on the effect of agricultural land use on water quality can be further divided into subcategories in two different ways. One way is based on the level of model aggregation and the size of study region. For example, there are a great number of studies that examine the effect of agricultural land use and practices on water quality at the field or watershed level. There are also studies that examine the issue at the regional or national level. An alternative way to categorize the studies is based on the various linkages they model. For example, many studies have modeled the effect of cropping patterns and farming practices on water quality, without examining how the decisions that led to that cropping patterns and farming practices were made. Other studies have systematically modeled the process from land use decisions to water quality.

It has long been recognized that agricultural land use and practices can cause water pollution and the effect is influenced by government policies (Just and Bockstael 1991; Wu and Segerson 1995). A major challenge to evaluating the effect is to account for the spatial heterogeneity of land quality and other physical characteristics. Land uses and farming practices vary from farm to farm, and affect water quality. In addition, because physical attributes of land are not homogeneous, water pollution can vary dramatically across farms that have the same land
use and farming practices. Climate also plays a role in determining the effect of land use and farming practices on water quality. Thus, it is necessary to identify the joint distribution of farming practices, land characteristics, and weather in order to determine the effect of land use and farming practices on water quality. Because spatial heterogeneity adds a spatial dimension to the analysis, it complicates the design of models intended to capture the impacts of land use on water quality.

A number of studies have examined the impact of agricultural land use and practices on water quality at the field, farm, or watershed levels (e.g., DeRoo, 1980; Hallberg 1989; Gilliam and Hoyt 1987; Tillman et al. 2002). These studies have linked water pollution to land use, fertilizer and chemical application rates, crop management practices, and topographic and hydrological characteristics. For example, in DeRoo (1980), nitrate concentrations in wells around and in shade tobacco tents and turf plots on two Connecticut farms were monitored. At one farm, less fertilizer was used. Nitrate concentrations averaged 2.5 mg/L in groundwater entering the farm and 4 mg/L leaving. After rainfall, concentrations in the downstream wells were found to be over 10 mg/L. At the other farm, intensive fertilizer application resulted in average year round nitrate concentration of 20 mg/L. DeRoo (1980) concluded that over-fertilization on easily leachable soils led to high nitrate concentration in well water downstream from the crop land. Gilliam and Hoyt (1987) examined nitrogen movement under different management practices. After an extensive literature review, Gilliam and Hoyt (1987) concluded that under no-till practices the amount of nitrogen in soil is higher than under conventional tillage practices. Thus, the use of no-till practices instead of conventional tillage increases the possibility of leaching. Conservation tillage practices, however, reduce nitrogen loss from surface run-off. The increased nitrogen in the soil makes more nitrogen available to leach to
groundwater. Anderson et al. (1985) examined the relationship between pesticide application rates and groundwater contamination of wells in Washington County, Rhode Island. Using data for individual wells, they regressed observed levels of contamination of the pesticide TEMIK (Aldicarb) on previous application rates and well characteristics. The well characteristics considered include depth to water and the distance of the well from the point of application. They found that contamination levels were significantly affected by application rates, with the effect decaying with both the well depth and the distance from the field.

The increased concern over water quality raises the issue about the scope and trend of water pollution from agriculture. To address the issue, several national inventories have been conducted in the United States to determine the status and trend of groundwater or surface pollution. These inventories have provided data for several summaries of water-quality conditions in the nation (e.g., Mueller et al. 1995; Omernik 1977). Smith and his associates (Smith et al. 1987) have assessed water quality trends in major U.S. rivers using water quality monitoring data. However, as Smith at al. (1987) point out, because the sampled pollutant concentrations come from both agricultural and non-agricultural sources, the extent to which changes in agricultural practices are reflected in the trends is largely a matter of conjecture. In addition, substantial variations in climate confounded assessment of water quality improvements that might have occurred because of changes in management practices. The groundwater quality monitoring in the Big Spring Basin in Iowa shows that, because nitrates tend to accumulate in the soil-water systems during a dry year and to be mobilized by the excessive precipitation and recharge in a wet year, changes in mean annual nitrate concentration parallel changes in groundwater discharge rather than changes in agricultural management practices (Rowden et al. 1995). However, this does not necessarily mean that agricultural land use and practices does not
cause water quality problems. Mueller et al. (1995) found that nitrate concentrations in 21% of samples collected beneath agricultural land exceeded the 10 mg/l maximum contamination level set by the U.S. Environmental Protection Agency. Nitrate-N is the most commonly detected agricultural chemical in groundwater.

The increased concerns over agricultural water pollution have also fueled the need for timely information on the location of areas with high potential for water contamination from agricultural chemical use. Several studies (Nielsen and Lee, 1987; Kellogg, Maizel and Goss, 1992; Wu et al., 1997; Wu et al. 1999) have attempted to provide this information by conducting national or regional assessment of water contamination potential from agricultural chemical use. Nielsen and Lee (1987) evaluated groundwater contamination potential from agricultural chemical use by synthesizing the USGS well-water test data, hydrological information and nitrogen use data. They found that the drinking water of an estimated 50 million people in the U.S. came from groundwater that was potentially contaminated from agricultural chemicals and that potential contamination follows regional trends, suggesting a need for targeting strategies. This study, however, did not incorporate production system information into the assessment.

Kellogg, Maizel and Goss (1992) developed a groundwater vulnerability index for nitrogen fertilizer to identify high-risk areas in the United States and updated their results in 1994 to incorporate revised estimates of precipitation and the 1992 National Resources Inventory data. They found that total number of high risk areas of pesticide leaching were 156.5 million acres in 1982 and 140.5 million acres in 1992. The chemical use was assumed to be the same for both years. Thus, the reduction in the high risk area of pesticide leaching was a result of changes in land use alone. Approximately one-half of this reduction was due to the enrollment of
cropland in the Conservation Reserve Program. One limitation of their index is that it does not incorporate crop management practice information (e.g., tillage and conservation practices), although it synthesizes physical data with land use data. Huang et al. (1992) estimated the distribution of cropland potentially vulnerable to nitrate-N leaching and found that the Corn Belt states have most of this cropland.

Wu et al. (1997) assessed potential water pollution from nitrogen use in the U.S. High Plains by synthesizing physical data with production system information, but used only a few representative soils to account for soil heterogeneity. They found that counties with great nitrogen losses tend to be those that are heavily furrow irrigated and/or have large acreage of corn. Their results suggest that targeting particular soils or production systems may be an effective strategy for protecting water quality, and that adopting modern irrigation technologies in heavily irrigated areas may be a key to reducing nitrogen water pollution.

Wu and Babcock (1999) developed a model to identify the spatial patterns of potential nitrate-N water pollution in the central U.S. and to estimate the effect of alternative farming practices on potential nitrate water pollution in the region. The model consists of a set of metamodels that summarize the impacts of soils, climate, crops, and management practices on potential nitrogen runoff and leaching. The potential for nitrogen runoff and leaching was estimated for a total of 128,591 sites using information on soil, climate, crop, rotation, tillage, irrigation, and conservation practices at each site. Thus, this assessment incorporates more detailed information on production systems and physical characteristics than previous assessments. For the 12 states in the Central U.S., the average annual N runoff and leaching, respectively, were estimated to be 5 kg ha$^{-1}$ and 3 kg ha$^{-1}$, which accounted for about 7% and 4% of total nitrogen applied. The potential for -N runoff was relatively high in much of the Corn
Belt, Kansas, and the Nebraska Platte River Basin, and the potential for N leaching was relatively high in Ohio, Indiana, and southern Illinois and Missouri. However, because much of the area with high leaching potential was tile drained, it is likely that a large portion of the leached N is discharged to surface water, rather than continue downward to groundwater.

3.2 Land use and biodiversity conservation

There is concern that we are in the midst of a human caused extinction crisis that has increased the current species extinction rates several orders of magnitude above the “natural” or background rate of extinction (Pimm et al. 1995). The destruction, fragmentation, and alteration of habitat for human land use are the leading causes of biodiversity decline (Soulé). Czech, Krausman, and Devers (2000) find that urbanization endangers more species in the mainland United States than any other human activity. Urbanization leads to an increase in human density in urban areas, and an associated increase in the concentration of buildings, roads, and fences. The resulting disturbances (noise, human presence, exotic species, habitat fragmentation, predation by pets) disrupt wildlife interactions and change wildlife populations and communities (Knight, Wallace, and Riebsame). Urbanization can also have a significant effect on species associated with remnants of habitat that are not directly altered, but are surrounded by development (Rottenborn). As a result, the species richness (the number of species) of many taxa is often found to decline along the urban-rural gradient, with the lowest richness found in the urban core.

There is a growing body of literature that examines the effect of land-use changes, in particular urbanization, on biodiversity (see McKinney (2002) for a review of this literature). For example, Friesen, Eagles, and Mackay (1995) and Rottenborn (1999) examine the effects of urbanization on bird communities. White et al. (1997) develop an approach to predict the
potential effects of landscape change on different biodiversity measures for terrestrial vertebrates. Montgomery et al. (1999) build on this approach to search for efficient land use allocations by estimating the marginal cost of increasing expected biodiversity.

### 3.3 Land use and carbon sequestration

Land use change such as agricultural intensification plays a significant role in the global carbon cycle, with two-way interactions. Any climate change from build-up of atmospheric greenhouse gases can affect land productivity and the allocation of land among major uses. In the other direction of interaction or feedback, increasing carbon sequestration in agricultural and other rural land uses is a potentially useful mechanism in global efforts to offset expanding greenhouse gas emissions. In many studies (e.g., Sedjo et al. 1993, 1995), changes in land uses (e.g., afforestation of agricultural land) are examined as the primary vehicle for expanding carbon flux.

A wide range of studies has examined how changes in land uses and land covers may affect the sequestration of atmospheric carbon by forests and other rural land uses, and how markets may affect the adjustment and adaptation of rural land uses to climate and ecological change (Sohngen 2007; Sohngen and Sedjo 2000, 2006; Sohngen and Alig 2000). Evidence from large-scale ecological models linked to atmospheric models suggests that the role of forests in the carbon cycle may become more important in the future (Neilson and Marks, 1994). For instance, forests may provide a positive or negative feedback to the carbon cycle, depending on the influence of the underlying climate change. Humans may attempt to mitigate the impacts of climate change by increasing the storage of carbon in forests through tree planting or altered agricultural practices. Although adaptation in land management is one important factor for gauging carbon flux feedbacks within the climate system, adaptation in product management can have important implications for how such adjustments manifest.
Most of the economic studies of carbon sink management evaluate policies that encourage the conversion of agricultural land to forests (e.g., Moulton and Richards 1990; Adams et al. 1993; Adams et al. 1999; Plantinga, Mauldin, and Miller 1999; Lubowski, Plantinga, and Stavins 2006; Parks and Hardie 1995). In these studies, the cost of the policy equals the opportunity costs of agricultural production and benefits are measured as physical quantities of carbon removed from the atmosphere. A consistent finding is that the costs of carbon sequestration through afforestation are comparable to, and in some cases lower than, the costs of alternative approaches such as fuel substitution and improved energy efficiency (Plantinga, Mauldin and Miller 1999; Stavins 1999; Lubowski, Plantinga, and Stavins 2006). However, only a few studies have investigated the additional environmental impacts of carbon sink management such as modification of wildlife habitat or reduction in run-off and leaching of agricultural chemicals (Plantinga and Wu 2003). If the additional environmental benefits or costs (“co-benefits”) of carbon sink management are found to be substantial, industrialized countries may want to adjust the mix of domestic mitigation and abatement strategies used to meet emissions reduction targets. In addition to carbon sequestration in forests, increasing the storage of soil carbon through agricultural management (e.g., conservation tillage) has also received attention in the literature because of its economic potential to improve soil fertility (Antle et al. 2003; Antle et al. 2007). Richards and Stokes (2004) reviewed studies on forest carbon sequestration cost and find that afforestation in the United States would sequester 250 to 500 million MgC annually at a price ranging 10–150 USD/MgC. By comparison, Antle et al. 2003), Capalbo et al. (2004), and Pautsch et al. (2001) suggest that conservation tillage can generate 0.25 to 6.2 million MgC in soil per year at the cost of 12–270 USD/MgC.
3.4 Integrate economic and biophysical models for policy analysis

Most of the studies discussed above focus on the effect of land use change and farming practices on environmental quality and ecosystems, without examining how the decisions that led to the land use change were made. These studies do not attempt to model land use decisions, but rather take these decisions as given and simply analyze their impact on water quality and other ecosystem services. To model the interaction between economic and ecological systems systematically, we must integrate economic and biophysical models to examine how economic and policy variables affect land use and how changes in land use in turn affect ecosystems.

A number of studies have systematically modeled the process from land use decisions to environmental impacts. These studies can be categorized into conceptual and empirical (or simulation) studies. The conceptual dimensions of land use and water quality have been explored in several studies, including Hochman and Zilberman (1978), Sharp and Bromley (1979), Shortle and Dunn (1986), Just and Antle (1990), and Opaluch and Segerson (1991). These studies show that agricultural and resource policies can affect agricultural production at both the intensive margin (changes in input use and management practices) and the extensive margin (changes in cropping patterns) and the resulting effects on water quality depend on physical attributes. These studies, however, do not provide quantitative estimates of the effects.

The empirical studies that model both land use decisions and their impact on water quality can also be classified into disaggregate models and aggregate models. The disaggregated models are generally site-specific and model micro-unit decisions and the water quality effect of these decisions at the farm or watershed levels (e.g., Jacobs and Casler 1979; Braden et al. 1989; Johnson et al. 1991; Taylor 1992; Wu et al. 1994; Helfand and House 1995). Because these
studies are site-specific, regional and/or national policy impacts cannot be easily derived from these studies without conducting similar analyses over other resource settings and aggregating to a larger scale.

The aggregate models can be further classified into two groups. One group integrates an aggregate economic model (usually a regional or national linear programming model) with a physical model to analyze the impact agricultural practices and policies on water quality (e.g., Piper et al. 1989; Mapp et al. 1994; Wu at al. 1995). The aggregate economic model predicts the impact of alternative policies on crop acres and input uses, and the physical model estimates the impact of crop production on water quality.

The second group of aggregate models examines policy impacts at regional or national level while incorporating site-specific land characteristics (e.g., Wu and Segerson 1995; Wu at al. 1996; Wu et al. 2004). For example, Wu et al. (2004) develop an empirical framework capable of measuring micro level behavioral responses and macro level landscape changes. The framework predicts farmers’ production practices and the resulting levels of agricultural runoffs at more than 42,000 agricultural sites in the upper-Mississippi river basin and is used to evaluate alternative conservation policies for controlling the hypoxia problem in the Gulf of Mexico.

4. Key Research Questions and Modeling Approaches

Land use change in general, agricultural intensification in particular, is arguably the most pervasive socioeconomic forces affecting economic and environmental systems. These forces drive a large portion of global economic and environmental problems. Solving these problems requires a renewed focus on land use modeling. Listed below are some key research questions.
The answers to those questions will contribute to a better understanding of the problems and will help society develop more effective strategies to address them.

**Technology adoption and agricultural intensification:**

1. What are the implications of labor-saving and biological technologies on agricultural intensification?

   *Suggested study area*: Bt. cotton in India, Pakistan; genetically modified maize in Brazil

**Interactions between agricultural intensification, economic growth and the environment:**

2. How does agricultural intensification affect farm income, rural economies, and rural socioeconomic structure?

3. How do economic development (e.g., from an agrarian economy to a mid-income country) and accompanying structural changes and urbanization in turn affect agricultural intensification?

4. How does agricultural intensification affect the environment and ecosystems?

5. How do changes in environmental quality in turn affect agricultural intensification?

   *Suggested study area*: Bangladesh, Vietnam, Uganda, Malawi, Tanzania

**Poverty, income inequality, and agricultural intensification:**

6. How do agricultural intensification and its interaction with economic development affect poverty rates and income inequality?

   *Suggested study area*: China, India, Vietnam

**The roles of agricultural intensification:**

7. Can agricultural intensification serve as a “smart strategy” to deal with global economic and environmental challenges (e.g., to feed the growing population, to protect the environment)?

   *Suggested study area*: all study areas suggested above
The lack of data and counterfactuals poses significant challenges to answering some of the research questions. Self-selection complicates the evaluation of a program’s impacts. In the context technology adoption, self-section occurs when a technology is more likely to be adopted by those who find it most helpful. For example, suppose bt-cotton is most useful to farmers who have a certain types of soils or weather conditions. A direct comparison of yields of adopters with those of non-adopters may over or under-estimate the effect of Bt-cotton on yields. Thus, when self-selection exists, the effect of technology adoption cannot be directly estimated by simply including a dummy variable in the regression. Switching regressing or polychotomous-choice selectivity models are some of the approaches that can be used to answer questions 1, 2, 4 and 6. Switching regression models have been applied to various economic issues. For example, Cooper and Keim (1996) and Fuglie and Bosch (1995) apply it to the adoption of farm management practices. Willis and Rosen (1979) apply the model to the problem of education and self-selection. But switching regression models can only be used to analyze dichotomous decisions. The polychotomous-choice selectivity model has at least two advantages over switching regression models (Wu and Babcock, 1998). First, it can be used to evaluate the effects of alternative combinations of management practices. Second, it accounts for both self-selection and the interaction between alternative practices. As such, it should provide more accurate estimates of the effects of individual conservation practices.

Endogeneity poses a significant challenge to empirical efforts that attempt to evaluate the interactions between agricultural intensification, economic growth and the environment. Although theoretically structural models can be used to specify the interactions, empirical estimation of such models requires assumptions regarding the distributions of unobserved variables, the choice sets, and the functional forms (Irwin and Wrenn, forthcoming). Even if a
robust empirical specification can be established, it still may be difficult to gather data on all of
the processes deemed important and to find the appropriate instrumental variables to address the
endogeneity issues. Nevertheless, structural modeling approaches firmly grounded in economic
theory provide a powerful framework for modeling interactions between agricultural
intensification, economic growth and the environment. They have tremendous potential for
policy evaluation when appropriate data are available.

5. Promising Study Areas and Data

Some promising research areas are suggested for each research question in the last section. The
selection of the promising study areas is based on the following two criteria. First, the research
questions must be highly relevant and important to the suggested study areas. For instance, to
explore the implications of labor-saving and biological technologies on agricultural
intensification, we should consider countries where biological technologies have been adopted.
Examples include Bt cotton in India and Pakistan and genetically modified maize in Brazil and
Argentina. To explore the interactions between agricultural intensification and economic
development and the accompanying structural changes and urbanization and how these
interactions affect poverty rates and income inequality, we need consider economies that are
under transformation such as China, India, and Brazil or economies that have potential for
transformation such as Vietnam. To explore the interaction between land use change/agricultural
intensification and ecosystem services, we should consider countries with rich natural resources
such as Vietnam and Brazil or countries that tend to rely on land conversions to meet the
growing demands for food, such as Malawi, Uganda, and Tanzania or countries.
The second most important consideration for selecting study areas is data availability. At micro-level, integrated household surveys, including community, agriculture, and household, are available in many of Sub-Saharan African countries (e.g., Malawi, Uganda, Tanzania) and some South and Southeast Asian countries (e.g., Bangladesh and Vietnam). Despite the comprehensiveness of this survey, there are some limitations about the data. For instance, agricultural intensification is not explicitly measured in these data; some important indicators of environmental quality, such as water pollution, cannot be found from these surveys. Table 2 provides a summary of the proposed study areas and data availability there.

The lack of data poses a significant challenge to addressing many of the key research questions relevant to agricultural intensification. In addition, self-selection and endogeneity make it difficult to identify program effects and causal relationships. Nevertheless, recent advancements in spatial modeling approaches have made it possible to overcome many econometric challenges. The convergence of interest and increasing availability of spatially explicit data have made the gains from research collaboration and cross-fertilization much greater. While the challenges are daunting, potential payoffs are large when correct answers to those research questions are found.
<table>
<thead>
<tr>
<th>Region</th>
<th>Country</th>
<th>Economy</th>
<th>Land resource endowment</th>
<th>Data type</th>
<th>Data period</th>
<th>Major crops</th>
<th>High-yielding variety technology</th>
<th>Biological technology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Uganda</td>
<td>Agrarian</td>
<td>70% 15%</td>
<td>National Panel Survey (community, agriculture, household)</td>
<td>1999, 2002, 2005, 2009</td>
<td>Cassava, maize, sweet potatoes, sugarcane</td>
<td>Maize</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tanzania</td>
<td>Agrarian</td>
<td>42% 37%</td>
<td>National Panel Survey (community, agriculture, household)</td>
<td>2008–2009</td>
<td>Cassava, maize, sweet potatoes, sugarcane</td>
<td>Maize</td>
<td></td>
</tr>
<tr>
<td>South Asia</td>
<td>Bangladesh</td>
<td>Agrarian</td>
<td>70% 11%</td>
<td>Integrated Household Survey</td>
<td>2011–2012</td>
<td>Rice paddy, potatoes, sugarcane</td>
<td>Rice</td>
<td></td>
</tr>
<tr>
<td></td>
<td>India</td>
<td>Under transformation</td>
<td>60% 23%</td>
<td>Unknown</td>
<td>NA</td>
<td>Sugarcane, rice paddy, wheat, potatoes</td>
<td>Rice</td>
<td>Bt cotton</td>
</tr>
<tr>
<td></td>
<td>Pakistan</td>
<td>Agrarian</td>
<td>34% 2%</td>
<td>Unknown</td>
<td>NA</td>
<td>Sugarcane, wheat, rice paddy, cotton</td>
<td>Rice</td>
<td>Bt cotton</td>
</tr>
<tr>
<td>Southeast Asia</td>
<td>Vietnam</td>
<td>Agrarian</td>
<td>35% 45%</td>
<td>Agricultural Census</td>
<td>2006 (2001 incomplete)</td>
<td>Rice paddy, sugarcane, cassava</td>
<td>Rice</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Vietnam</td>
<td>Agrarian</td>
<td>35% 45%</td>
<td>Household Living Standard Survey</td>
<td>2008 (2002, 04, 06 incomplete)</td>
<td>Rice paddy, sugarcane, cassava</td>
<td>Rice</td>
<td></td>
</tr>
<tr>
<td>East Asia</td>
<td>China</td>
<td>Under transformation</td>
<td>56% 22%</td>
<td>Different sources, province-, county-level &amp; 1 km pixel level</td>
<td>Multi-period, unbalanced</td>
<td>Maize, rice paddy, sugarcane, wheat, potatoes, sweet potatoes</td>
<td>Multiple crops</td>
<td>Bt cotton</td>
</tr>
<tr>
<td></td>
<td>Brazil</td>
<td>Under transformation</td>
<td>33% 61%</td>
<td>Unknown</td>
<td>NA</td>
<td>Sugarcane, maize, soybeans</td>
<td>GM maize</td>
<td></td>
</tr>
</tbody>
</table>
References


42. Hardie, W., T. A. Narayan, A. Tulika, and B. L. Gardner. “The Joint Influence of Agricultural and Nonfarm Factors on Real Estate Values: An Application to the Mid-


106. Segerson, K. "Incentive Policies for Control of Agricultural Water Pollution."


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APPENDIX

Table A1. References on the Effect of Land Use and Land Use Change on Watershed Health Indicators

**Conventional ambient water quality**


**Toxic ambient water quality**


Aquatic and wetland species at risk of extinction


Source: Hascic and Wu (2006)