PREDICTING THE SUPPLY OF ECOSYSTEM SERVICES FROM AGRICULTURE

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A socially efficient agricultural policy would provide incentives for farmers to supply the appropriate combination of market and nonmarket goods demanded by society (Antle and Capalbo 2002). Ecosystem services (ES) are the most important type of public goods provided by agriculture. To support the transition from commodity-based subsidy policies to policies based on the efficient provision of ES, policy decision makers will need to know how to design efficient mechanisms for the provision of ES from agriculture, and will need estimates of their environmental and economic effects. For example, the 2002 Farm Bill created the Conservation Security Program, which pays farmers who adopt environmentally beneficial practices. The ten-year costs of implementing this program were estimated to be \$2.1 billion in 2002, but rose to \$8.9 billion in 2004. This cost underestimation was due in part to inaccurate estimates of farmer participation (General Accounting Office 2006). This example suggests that estimates of benefits and costs of these policies with a reasonable degree of accuracy will be needed to facilitate the transition to policies based on provision of ES. At the same time, to be useful for policy decision making, information needs to be provided in a timely manner. Researchers will inevitably need to trade-off cost, timeliness, and accuracy in making decisions about the appropriate modeling approach.

The purpose of this paper is to present a conceptual framework for the analysis of ES supply, and to discuss some of the data and modeling issues that arise in predicting farmers' participation in ecosystem service contracts and the supply of ES resulting from them. Two key features of agro-ecosystems that have been identified in the scientific literatures are the complexity of the biophysical and human environments in which they operate, and the complexity of the ecological and economic processes governing the systems. To frame the discussion, we outline a model of the supply of ES that illustrates the ways that spatial and system complexity can affect it. We use this model to discuss the data and modeling issues that arise in empirical implementation. We conclude with recommendations regarding modeling strategies that can provide sufficiently accurate and timely information needed to support informed policy decision making.

A Model of the Supply of Ecosystem Services

In this section we use a simple static model to estimate the supply of ES. This model demonstrates that the supply of ES generally depends on: (1) the spatial distribution of returns for competing land use and management activities; (2) the spatial distribution of ES associated with the competing practices; and (3) the design of the incentive mechanism embodied in the contract.

We consider a farmer's choice between two competing land uses or management practices, a and b, in a geographic region. The different land uses are expected to yield different combinations of marketable product and ES. The land-use decision in each time period is based on the farmer's goal to maximize expected economic returns to the land. We initially assume there are no costs of switching from practice a to practice b, and discuss relaxing that assumption later. Under these assumptions, activity a is chosen if it yields higher expected returns than activity b, otherwise b is chosen. Let the difference in returns per hectare between the

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two practices (returns to a minus returns to b) be denoted as $\omega(p, s)$, where p represents output and input prices and s denotes the site. Thus, the farmer adopts practice a if $\omega(p, s)$ is positive, and adopts b otherwise. We can interpret $\omega(p, s)$ as the opportunity cost per hectare, in terms of forgone returns, for adopting practice b.

We assume that an ecosystem service of $e(s)$ units per hectare per time period is produced at each site s when practice b is in use, and that zero services are produced if practice a is in use at the site. Here we treat e as a scalar for convenience, but it is important to note that in many cases multiple ES may be produced at a site (Plantinga and Wu 2003). In principle, each of the services can be priced and quantified, although in practice it is often difficult to do so. It should be noted that some processes determining $e(s)$, such as soil carbon sequestration, are spatially independent, whereas in other cases such as habitat preservation or water quality protection there may be spatial dependencies. These spatial dependencies will need to be taken into account in designing an efficient mechanism for provision of the service. Similarly, there may be spatial dependencies in opportunity costs if, for example, there are positive learning externalities associated with the adoption of alternative management practices.

In the private equilibrium that occurs without any positive incentives to supply e, farmers will simply allocate land to the use with the highest private returns. To increase the supply of ES above the quantity provided in this private equilibrium, a payment is offered to the land managers by a private or government entity for increasing the quantity of the ecosystem service.[1] Abstracting from issues such as data availability and costs of verifying compliance with contracts, the most efficient payment mechanism would be based on the amount of the environmental service produced. However, most current conservation and environmental programs in the United States and Europe pay farmers based on the adoption of practices. Some programs, such as the Conservation Security Program in the United States, pay farmers for a set of practices that are presumed to be related to a set of ES. It is also possible that the two types of mechanisms would be combined, so that farmers participating in an ES contract would be paid per unit of service, but also would be required to adopt specified practices. The U.S. Department of Agriculture has attempted to increase the efficiency of programs such as the Conservation Reserve without actually quantifying service flows by linking payments to site-specific conditions, such as proximity to surface water, that are known to be associated with the amount of a service such as water quality protection.

The quantity of ecosystem service supplied at each site is not known *ex ante*, so incentives must be based on expected ES or on adoption of practices. The farmer can choose practice a and receive the expected returns to that activity, or can choose practice b and receive the expected returns to b plus the ecosystem service payment $g(s)$. When payments are per unit of ecosystem service, $g(s) = p_e e(s)$, where e is interpreted as the expected amount of services produced with practice b, whereas if payments are made for adoption of practices, $g(s) = g_b$. The farmer will choose activity b if the net benefit n of changing practices is positive,

$$(1) \qquad n = g(s) - \omega(p, s) > 0$$

and will choose practice a otherwise.

Farmers' site-specific land use decisions generate a regional supply of ES that is determined by the joint spatial distribution of ES and opportunity cost. Define the spatial distribution of net benefit as $\phi(n)$. For $g = 0$, the area under the positive tail of $\phi(n)$ represents those land units where farmers use practice b without ecosystem payments. Define the quantity of ecosystem service supplied in this initial equilibrium as $S(p)$. As g increases, n becomes positive for additional land units, farmers adopt practice b on those land units, and the quantity of ES supplied becomes greater than $S(p)$. Let the size of each site (management unit or field) be a hectares, and order sites according to their net benefits for given prices. The expected supply of ES is then given by

$$(2) \qquad S(p, p_e) = S(p) + \int_0^\infty a\, e(n)\phi(n)\, dn.$$

When the payment is based on practices, the implicit price or marginal cost of the ecosystem service is equal to the payment g_b divided by e on the marginal land unit entered into the contract. Thus, in the case

[1] Without loss of generality, we assume that farmers are paid only for an *increase* in environmental services relative to a baseline. Also note that an efficient incentive system would pay farmers a positive price for increasing environmental services and tax them for any actions that reduced them. This type of symmetric incentive could be modeled in essentially the same way as the positive incentive example presented here.

of payments for practices, we interpret p_e in equation (2) as the implicit price. Abstracting from costs of implementing contracts, payments per unit of ES are known to be the most efficient incentive mechanism, hence the supply curve based on payments per unit of ES lies to the right of a supply curve based on a less efficient mechanism (Antle et al. 2003).

The properties of the supply curve (2) are also determined by the form of $\phi(n)$ which is derived from the distributions of ω and e. When $g > 0$, $\phi(n)$ is a convolution of the distributions of ω and e. The particular form of $\phi(n)$ will depend on the processes generating the site-specific quantities of e and ω. For example, if there are no spatial dependencies between these processes, the distribution of e can be defined independently of the incentives provided to farmers. If payments are made per unit of ES the mean and higher moments of n can be derived from the moments of e and ω using standard formulas for linear combinations of random variables. When payments are based on practices, g is constant, $\mathrm{E}(n) = g_b - \mathrm{E}(\omega)$, and the higher moments of n and ω are equal.

In addition to the opportunity cost of changing practices represented by forgone returns, there may be other costs of adjustment associated with changing practices. These costs of adjustment may involve capital investments or learning about alternative management practices. In addition to adjustment costs, there may be a variety of other behavioral and institutional factors that influence farmers' willingness to change land use and management practices. There is a sizeable literature on the adoption of conservation practices in agriculture that is closely related to the problem of ecosystem service supply. The literature shows that characteristics of farm decision makers affect their willingness to adopt conservation tillage, although how they impact decisions appears to depend on their geographic location and other factors (e.g., Fuglie and Kascak 2001). In addition, the literature on technology adoption shows that risk and uncertainty effectively raise the perceived costs of changing practices (Sunding and Zilberman 2001). Risk is most likely to impact decision making when there is a substantial difference in risk associated with the land use options, for example, as would be the case when farmers are choosing between risky crop production and a riskless government payment for idling land.

Another factor that is likely to affect farmers' willingness to participate in ecosystem service contracts is transaction costs. These costs include the time and other resources farmers spend learning about the ecosystem service contract, as well as costs of verifying compliance with the contract. In addition, when the processes governing the provision of ES are spatially dependent, efficient provision may require cooperation among groups of farmers within an agro-ecological zone (AEZ). These coordination costs are likely to depend on factors such as the number of farms participating, the number of hectares under contract, and the number and frequency of verification measurements required for contracts. If these costs are allocated to participants according to the number of hectares under contract, then the net benefit of contract participation (equation (1)) is modified by subtracting transaction costs. If these transaction costs do not vary spatially, they simply shift the mean of the spatial distribution of net benefits in the negative direction. Defining adjustment costs and other costs of adoption as c_a and defining transaction costs as c_t, we can write equation (1) as

$$(3) \qquad n = g(s) - \omega(p, s) - c_a - c_t.$$

Dividing this expression by the rate of ecosystem service, and replacing the payment g with the expression $p_e\, e$, shows that the farmer will participate in a contract when

$$(4) \qquad p_e > \omega(p, s)/e - (c_a + c_t)/e.$$

Thus, the farmer will participate in a contract when the price exceeds the opportunity cost per unit of ecosystem service. Fixed adoption and transaction costs per hectare have the effect of creating an adoption threshold. Equation (4) shows that these adoption and transaction costs will be particularly important when the price of ES is low and in regions where the rate of ES is low.

Data and Modeling Issues

The preceding discussion shows that the properties of the ES supply curve (2) are determined by the type of incentive mechanism and the properties of $\phi(n)$. The scientific challenge is to assemble data and models needed to characterize $\phi(n)$ and thus construct the ES supply curve with an adequate degree of accuracy needed to support informed policy decision making.

For purposes of organizing our discussion, it will be useful to describe the data and the

		System Complexity	
		Low	High
Spatial Complexity	Low	Minimum Data Models	Representative Coupled Disciplinary Models
	High	Site-Specific Minimum Data Models	Site-Specific Coupled Disciplinary Models

Figure 1. Spatial complexity, system complexity, and model design

processes being modeled in terms of their spatial and model complexity. Although there are varying degrees of complexity in both of these dimensions, for purposes of this discussion we will refer to low and high degrees of complexity, as shown in figure 1. The vertical dimension in figure 1 represents degrees of complexity in the biophysical and economic conditions in the geographic region being studied. Spatial complexity refers to the spatial heterogeneity and dependence observed in biophysical conditions (e.g., topography, soils, and climate) as well as in economic and related human dimensions (e.g., prices and market institutions). Model complexity refers to features of model processes such as nonlinearity, dynamics, feedbacks, and spatial dependence. We now consider the modeling approaches suggested by this scheme.

High Spatial and System Complexity: Coupled, Site-Specific Disciplinary Models

Ecological and economic complexities suggest the need for data and models that are spatially explicit. Most ecological and economic processes are also dynamic, and feedbacks between ecological and economic processes, as well as spatial dependence between processes, may be important (Sanchirico and Wilen 2005; Antle and Stoorvogel 2006). As demonstrated by recent contributions to the literature, given sufficient spatially referenced data, it is possible to parameterize and simulate coupled biophysical and econometric models so as to characterize $\phi(n)$ for policy analysis of certain types of ecosystem service such as carbon sequestration and water quality protection (e.g., Pautsch et al. 2001; Antle et al. 2003; Wu et al. 2004; Lubowski, Plantinga, and Stavins 2005).

It is important to distinguish between the spatial properties of the biophysical and human populations (represented by the vertical dimension in figure 1) and the properties of the data that are available to represent those populations. Site-specific biophysical and economic data with the geographic coverage needed for analysis of agriculture-environment interactions are exceptional. The available spatially referenced data, such as the National Resources Inventory data in the United States, have many limitations for modeling both ecological and economic processes (Paustian et al. 2006). Notably, the NRI data do not provide adequate economic information about management practices and costs of production needed to model ecosystem processes and estimate the opportunity cost of changing practices. Another potential source of data in the United States is the agricultural census, but due to confidentiality restrictions a farm's location cannot be disclosed, and cost of production data are not disaggregated by production activity. Both the NRI and the agricultural census are collected at five-year intervals, so they do not provide information needed to characterize system dynamics. In most cases, site-specific economic data are only available from special-purpose farm surveys, and the time and resources required to undertake special-purpose surveys precludes their use for most policy analysis. When special-purpose survey data are available, they usually cover limited geographic areas and time periods, so they often do not cover the geographic area needed for regional or national policy analysis.

There are also important limitations in data needed to implement biophysical simulation models. Often soils data are not available with high enough resolution to model crop production and environmental processes on a site-specific basis (i.e., by management unit such as a farmer's field) leaving researchers to use representative soil profiles and closest weather stations or spatially interpolated data. When data are available at a high spatial resolution (e.g., the Soil Survey Geographic Data Base provided by the USDA Soil Conservation Service) the quantitative soil properties needed for simulation models may be lacking. Climatic data can be even more problematic, because such data are collected at weather stations that may not be located near a given site, and because processes such as rainfall can be highly location specific and dependent on topography.

Although advances in disciplinary models and data acquisition methods are being made continuously, it nevertheless remains true that the ability of the scientific community to model agricultural systems as complex, dynamic, spatially explicit systems is limited. Most such efforts involve a simple coupling of disciplinary models without a full integration of the dynamics of the subsystems (Antle et al. 2001). Due to these data limitations, researchers need to devise data and model simplifications that nevertheless allow sufficiently accurate estimates of ES supply curves.

Low Spatial and System Complexity: The Minimum Data Approach

At the opposite end of the complexity spectrum are cases in which the biophysical and human populations can be characterized with sufficient accuracy using simple statistical parameterizations. Similarly, in some cases the ecological and human decision-making processes can be characterized in relatively simple terms. In such cases, it is possible to use what we shall describe as a minimum-data (MD) approach to model spatial distributions of ES and opportunity cost. As defined by Antle and Valdivia (2006), the MD approach utilizes a simple parameterization of $\phi(n)$, and then estimates those parameters using available data. They applied the approach to the analysis of soil carbon sequestration in the dryland wheat system typical of the U.S. Great Plains region, which had been carried out earlier with a spatially explicit economic simulation model (Antle et al. 2003). They found that the MD approach provided a close approximation to the carbon supply curve derived from the more complicated model.

In the biophysical dimension, soils and climate were characterized by AEZ's and the Century ecosystem model was used to estimate an expected carbon rate for each AEZ associated with changing management practices in spring wheat production from a crop-fallow rotation to continuous cropping. Thus, within each AEZ, all farmers participating in carbon contracts were assumed to use the same carbon rate estimate to decide whether or not to participate in carbon contracts. However, the Century model is a complex, mechanistic, dynamic simulation model that may be more elaborate than necessary to estimate carbon accumulation rates under conditions where spatial complexity is low. Simpler empirical models have been developed for carbon sequestration modeling that could be utilized under these conditions (Ogle, Breidt, and Paustian, 2003; Grace and Merz 2001).

In the economic model, a static expected profit maximization model was used to characterize the opportunity cost of changing practices. The spatial distribution of opportunity cost was assumed to be normally distributed. The mean was estimated for each AEZ by utilizing mean differences in costs and returns. The variance was estimated by using the spatial variation in yield to approximate the spatial variation in opportunity cost together with plausible assumptions about the spatial correlation between practices. Farmers can readily change from a crop-fallow rotation to continuous cropping without significant capital investment or learning, so the contract participation decision was represented as a simple static decision, whereas in other cases it might be necessary to consider adoption dynamics and capital investment decisions. Since the expected carbon rate was assumed to be equal across all land units in each AEZ, $\phi(n)$ could be defined for each carbon price as equal to the spatial distribution of opportunity cost adjusted for the carbon payment.

A key insight underlying the MD approach is that it may not be necessary to model the ecological and economic processes on a site-specific basis to approximate $\phi(n)$ sufficiently well for policy analysis. However, it is important to keep in mind that while the MD approach may work well for analysis of ES service supply estimation, it may be inadequate for more general policy analysis. For example, a key limitation of the MD approach is that it provides an estimate of the ES supply curve given all other prices (see equation (2)). To estimate the shift in the ES supply curve caused by a change in other prices, a more complete economic model would be needed that explains how the distribution of opportunity cost changes with those other prices.

High Spatial Complexity and Low System Complexity: Site-Specific MD Models

As the MD example described above suggests, in many cases it will be possible to represent much of the spatial heterogeneity by simply stratifying a region into subregions or AEZ's that can be defined in terms of key spatial criteria such as slope, altitude, proximity to surface water, distance to roads, and so on. When the ecosystem service or opportunity cost varies continuously, arbitrary stratification may be inappropriate, but the system complexity may nevertheless be low. In such cases, if spatially explicit data are available, it is still possible to use the MD approach by using a simple but spatially explicit parameterization of $\phi(n)$. For example, when payments are made per unit of ecosystem service, then from equation (3), $n = p_e e - \omega - c_a - c_t$. Assuming adjustment costs and transaction costs do not vary spatially, it follows that the mean of n is a function of the means of e and ω and the variance of n is a linear function of the variances and covariance of e and ω, and higher-order moments can similarly be calculated. If site-specific data are available, then instead of estimating a regional mean for ω, a simple reduced-form parametric model of the moments of ω can be estimated as a function of site-specific characteristics and used as the basis for simulation.

Low Spatial Complexity and High System Complexity: Representative Farm Models

This case represents many agricultural system models in the agricultural economics and related literatures. For example, there are many examples in which system complexities such as land allocation among multiple crops and crop rotation dynamics are modeled, but "representative" data from AEZ's or other spatial units are used. These more complex economic models also may be coupled with biophysical process models (e.g., McCarl and Schneider 2001). A principal limitation of this approach is that the assumption of low spatial complexity is often made out of convenience or due to data limitations. When the population being modeled is in fact spatially complex, the use of a representative ecological model or economic model can produce a poor approximation to the ES supply curve. For example, Antle et al. (2007) found that using an average soil carbon rate to estimate a regional carbon supply curve for 1,500 counties in the central United States provided a reasonable approximation to the supply curve for the entire region, but resulted in large prediction errors in subregions.

Conclusions

In this article we present a conceptual framework for the analysis of the supply of ES. This framework shows that the supply function is derived from the spatial distribution of ES and the spatial distribution of opportunity cost of providing those services by changing agricultural land use and management practices. The scientific challenge is to assemble data and models needed to characterize these spatial distributions and thus construct the ES supply curve with sufficient accuracy to support informed policy decision making. We describe the populations and processes generating these spatial distributions in terms of their complexity. Except in rare cases, due to both data and model limitations it is not possible to derive the spatial distributions of ES and opportunity cost using spatially explicit coupled disciplinary models, and the level of accuracy needed for policy analysis may not require this level of data and model detail. Therefore, simpler methods that provide adequate approximations are needed. We discuss an alternative, minimum data approach that is based on using relatively simple empirical approximations to the relevant spatial distributions. While further research will be needed to assess the adequacy of this type of simpler modeling approach in different ecological and economic settings, we hypothesize that this type of approach may often suffice and in fact be the only one feasible to support policy decision making, given time and other resource constraints.

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