

Integrating Economic Land-Use and Biophysical Models

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Abstract

Land-use change is a leading cause of environmental degradation in terrestrial systems and has important implications for natural resource use. Economists have a long tradition of studying land use and in recent decades have developed empirical land-use models using econometric and optimization approaches. Integration of these land-use and biophysical models allows for a more comprehensive analysis of the consequences of future land-use change and the use of land-use policies to avoid undesirable outcomes. I provide a conceptual framework for the modeling approach, describing the individual components of an analysis as well as how they are linked together. My review describes how the literature has evolved to take advantage of spatial data and greater computing capabilities. Although most researchers have used either an econometric or an optimization approach, there is potential to combine these methods to identify more efficient land-use policies that still meet criteria of tractability and political acceptance.

1. INTRODUCTION

Land-use change is an important cause of environmental degradation, contributing to biodiversity loss (Sala et al. 2000, Wilcove et al. 2000), increasing atmospheric carbon dioxide concentrations (van der Werf et al. 2009), and loss of open space (Lubowski et al. 2006b). Land use has important implications for the use of natural resources, such as water for irrigation, and can influence risks and consequences of natural disasters (Hey & Philippi 1995, Syphard et al. 2007) and infectious diseases (Patz et al. 2004). Economists have a long tradition of studying land, which has provided a framework for understanding and modeling the determinants of land-use change (von Thünen 1826, Alonso 1964). Integration of economic land-use models with landscape-scale biophysical models allows for a more comprehensive analysis of the consequences of future land-use change and the potential for using land-use policies to avoid undesirable outcomes.

Biophysical models represent biological and physical processes in the environment. A simple biophysical model is a yield curve relating plant growth to temperature and rainfall. Another example is the universal soil loss equation, which is a simple mathematical model used to describe the relationship between erosion and biophysical values such as rainfall, soil characteristics, topography, and land management. From a biophysical perspective, land-use change alters natural processes in ways that affect living organisms. For example, removal of riparian vegetation for timber or land conversion to crops can increase stream temperatures and, thus, affect fish populations (Schlosser 1991). Urban development can contribute to the urban heat island effect (Stone & Rodgers 2001), which has important consequences for human health (Patz et al. 2005). At the heart of more complex biophysical models such as RHESSys (Tague & Band 2004) and CLM (Dai et al. 2003) are GIS-based representations of the landscape, which include fine-scale information on land cover. Land cover maps provide a direct means of linking to economic land-use models.¹

Economists have developed two basic types of empirical land-use models. The first is econometric land-use models, which relate observed private land-use decisions to economic variables such as land rents. These models have been developed with aggregate land-use data (e.g., Stavins & Jaffe 1990, Plantinga 1996), plot-level data (e.g., Lubowski et al. 2006a), and spatially explicit data (e.g., Carrion-Flores & Irwin 2004). A second type comprises optimization models, which seek to solve for an optimal spatial arrangement of land uses, such as conservation lands (Polasky et al. 2008), or to find land-use allocations corresponding to competitive market equilibria (Adams et al. 1996). Although land-use models are developed by researchers in other fields, such as geography (Clarke & Gaydos 1998) and ecology (Theobald 2005), economic models have the advantages of being grounded in a theory of individual decision making (e.g., Miller & Plantinga 1999) and of providing a framework for policy analysis. In particular, economic models can be used to evaluate the effects of incentives designed to encourage particular land uses (e.g., Plantinga et al. 1999, Lawler et al. 2014) or to evaluate the benefits and costs of land-use policies (Alig et al. 1997, Polasky et al. 2008).

The purpose of this review is to describe methods for integrating economic land-use and biophysical models. We emphasize models that evaluate the provision of ecosystem services from private lands, although many of the approaches we discuss can be applied to public lands as well. The next section provides an overview of the general modeling approach. An important distinction is made between econometric and optimization models, as these models are linked with biophysical models in different ways. Subsequent sections are devoted to discussing the model components and the connections among them in more detail. Although much of this discussion

¹Land cover is a physical description of land (e.g., its vegetative cover is forests), whereas land use indicates how humans are using the land (e.g., for commercial forestry).

emphasizes what has been done in previous studies, attention is also given to ways that models can be improved and extended. We do not attempt to provide a comprehensive review of all integrated land-use studies; rather, we highlight studies that nicely illustrate the methods used in this literature. A final section provides discussion.

2. OVERVIEW OF MODELING APPROACH

Figure 1 shows a schematic diagram of integrated land-use and biophysical models. As indicated at the top of the figure, policy is an input to econometric and optimization models. Examples include a per-acre subsidy for conversion of agricultural land to forest and a budget for establishing a network of conservation reserves.

Under the econometric approach, analysis of the policy yields a prediction of how land use would change under the policy. Such predictions might take the form of a map showing where on the landscape these changes occur or simply an aggregate summary of area changes by use. Changes in land use are then evaluated in a biophysical model. For example, the biophysical model may produce estimates of the additional carbon sequestered in forests or estimates of the change in survival probabilities for a group of species. The next step is to represent these changes in economic terms by combining information from the econometric land-use model with changes in biophysical variables. Because econometric models are formulated in terms of economic variables such as rents, they yield information on the opportunity costs of the policy. Thus, one might estimate the cost of improving water quality through a policy that penalizes land conversion in riparian areas.

There are potential feedbacks from land-use and biophysical models to econometric land-use models. In the first case, if changes in land use affect prices for crops and other commodities, then

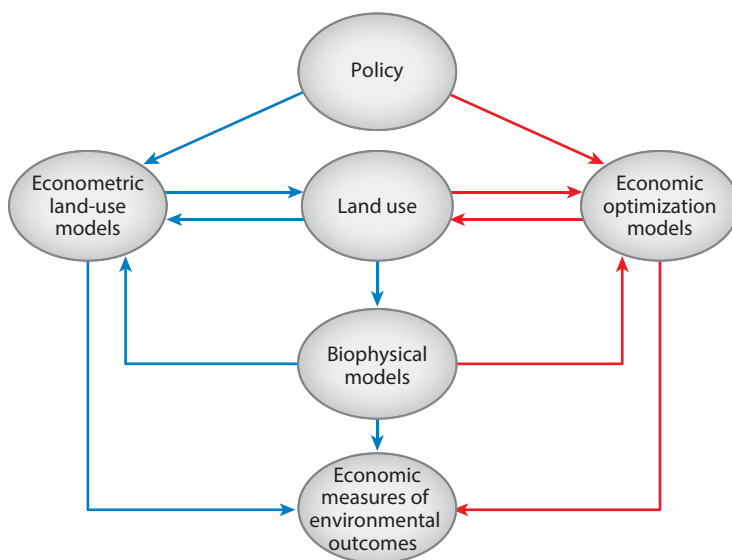


Figure 1

Integrated economic land-use and biophysical models. Ovals correspond to model components, and arrows indicate linkages between them. Blue and red arrows are used to distinguish between econometric and optimization approaches, respectively.

rents are endogenous, and solving for equilibria in commodity and land markets becomes necessary. The feedback from biophysical models reflects the possibility that changes in the environment will affect land-use choices. For example, policies that produce amenities such as open space may increase nearby housing rents, thereby increasing incentives for residential development. Increases in water quantity may spur the conversion of land to irrigated agriculture.

The information flow under the optimization approach differs from that under the econometric approach. An optimization model typically incorporates information on land use and biophysical variables at the outset. For example, in a reserve site selection problem, the objective may be to maximize the number of species protected on the landscape subject to a budget constraint that limits the number of acres that can be conserved. This approach requires that information on initial land use and species be brought into the optimization model, as shown in **Figure 1**. The solution to the optimization problem is an optimized landscape, which can be summarized using economic measures such as production possibilities frontiers. The two-way arrows between the land-use component and the optimization model reflect the potential for land rents to be endogenous, as in sectoral optimization models that solve for land market equilibria.

3. MODEL COMPONENTS AND LINKAGES

3.1. Policy

Under the econometric approach, the most common policies analyzed are per-acre subsidies that raise the relative returns from desired land uses. In most cases, the ultimate policy objective is to increase services from the land, such as carbon sequestration or wildlife habitat, rather than the area of land in particular uses. However, because these environmental services are typically public goods, one cannot directly model the private supply of these services by using econometric methods. Thus, private land-use decisions are modeled in terms of returns to private goods produced from the land (e.g., timber, crops), and policies are directed at augmenting or diminishing these returns.

Plantinga et al. (1999) and Lewis & Plantinga (2007) use econometric land-use models to evaluate the effects of per-acre subsidies for forestland. Stavins (1999) notes that an afforestation subsidy may encourage landowners to take land out of forest so that they can receive the subsidy for converting it back. To deter inefficient land conversions, he evaluates a two-part incentive that pays a subsidy for afforestation and levies a tax on deforestation. In a related approach, Fezzi & Bateman (2011) develop econometric models of land shares in different agricultural uses and include input prices as exogenous variables. This approach enables them to simulate the effects on land use of a tax on nitrogen fertilizer. Mason & Plantinga (2013) recognize that because uniform land-use subsidies provide landowners with inframarginal rents, such subsidies may involve large transfers from the government. These researchers evaluate a contract policy that minimizes the planner's ex ante expenditures on payments to landowners.

Besides changing the allocation of land among the existing set of uses, policies can also be designed to encourage new uses. Using econometric methods, Lewis et al. (2011) estimate the payments needed to compensate landowners for removing land entirely from agricultural production and putting it into conservation. With an econometric model of land-use shares, Bateman et al. (2013) evaluate policies requiring agricultural land set-asides and land diversions for parks.

Under the optimization approach, the policy objective is usually stated in terms of a biophysical target. Rabotyagov et al. (2010) find least-cost ways of achieving specified reductions in nitrogen and phosphorus loadings in the Gulf of Mexico. The choice variables in this optimization problem are various agricultural practices as well as retirement of cropland. In Polasky et al. (2008), the

objective is to find land-use patterns that maximize an aggregate biodiversity score. The problem is constrained by a budget specified in terms of the total value of land within the region. Newburn et al. (2006) consider the problem of a planner who seeks to purchase development rights that restrict future residential and vineyard development. The objective is to maximize open space and habitat benefits subject to a constraint on total expenditures on conservation easements. Sectoral optimization models can also be used to evaluate policies stated as biophysical targets. Alig et al. (1997) examine the welfare implications of meeting specified carbon targets, expressed as changes in consumer and producer surplus relative to a baseline. Instead of using a biophysical target, Khanna et al. (2011) introduce a range of biomass prices to estimate the supply response for different cellulosic biofuels.

3.2. Econometric Land-Use Models

The theoretical basis for econometric land-use models is a model of profit maximization by individual landowners. Each landowner is assumed to allocate a land parcel of uniform quality among the set of available uses to maximize profits, or what are often referred to as returns (or net returns) in the land-use literature.² Returns can be defined for the current period alone (e.g., Wu & Segerson 1995) or as the present discounted value of the stream of returns (e.g., Stavins & Jaffe 1990). The latter approach is required if annual returns to alternative land uses occur with different periodicities, as with agriculture and forestry. The dynamic model of optimal land allocation requires an explicit assumption about how landowners form expectations about future returns. As Plantinga (1996) shows, if landowners have static expectations—that is, their expectation is that future annual returns to their land are constant—they will allocate each land parcel to the use generating the greatest annualized returns net of conversion costs. Relaxing this assumption complicates the estimation problem considerably because this simple decision rule no longer applies generally. De Pinto & Nelson (2009) assume that farm commodity prices follow an autoregressive process, which requires that they estimate a structural dynamic model of land-use change following Rust (1987).

If the land-use model is estimated with aggregate (e.g., county-level) data on land use, then the individual land-use decisions need to be aggregated to match the scale of the data. Aggregation can be done by assuming a representative landowner or constant returns to scale (Fezzi & Bateman 2011) or by integration of county land quality densities (e.g., Lichtenberg 1989, Hardie & Parks 1997). The result is a land-use share model, which specifies the share of land in each use within the aggregate area as a function of average profits obtained from each use. The share model is a static or long-run model and thus does not account for transitions between uses or the costs associated with land conversion. Stavins & Jaffe (1990) and Plantinga & Ahn (2002) develop models that account for transitions between uses and can be estimated with aggregate data.

If data are available on a random sample of land plots, then aggregation is not required. A number of authors estimate multinomial logit models of land-use decisions using plot data (e.g., Lubowski et al. 2006a, Lewis & Plantinga 2007). An advantage of these models over aggregate models is that they accommodate plot-level variables, such as measures of land productivity. Moreover, if repeated observations are available, then land-use transitions can be explicitly modeled. However, these models still require an assumption of constant returns to scale because information is available only about individual land plots, and not about larger operations of which

²In empirical land-use applications, returns are typically measured as the net revenues (total revenues minus total costs) from the production of commodities.

the plot might be a part. With many data sets, the precise location of land plots is not revealed to protect confidentiality. For example, the National Resources Inventory reveals only the county within which a plot is located (US Department of Agriculture 2013). Use of such data limits the precision with which returns to land can be measured. Lubowski et al. (2006a), for example, include measures of county-level average returns, along with plot-level measures of land quality.

The availability of spatially explicit data on land use obtained through remote sensing has allowed researchers to model the determinants of land-use decisions with much greater precision. In an early application, Bockstael (1996) uses land-use maps for two time periods to model the transition of land from undeveloped to developed use. To obtain estimates of returns to development, she estimates a hedonic function of land sales and uses this model to predict development returns for each grid cell. An appealing feature of this approach is that the hedonic model can be estimated with a small sample of parcels but still be used to generate spatially varying estimates of returns for all the parcels in the land-use analysis. Prediction for all parcels is accomplished by including spatial variables in the hedonic model, such as distances to roads and land quality measures, and then using maps of these variables to produce a map of estimated returns. An alternative is to skip the estimation of the hedonic model and instead directly estimate a reduced-form land-use model specified in terms of spatially varying parcel attributes (Carrion-Flores & Irwin 2004, Newburn et al. 2006). This approach has lower data requirements but has two disadvantages relative to Bockstael's two-stage method. First, the land-use model is not specified as a function of returns, which limits its use for evaluating market-based incentive policies. Second, if a linear hedonic model is estimated in the first stage, then techniques such as fixed effects and instrumental variables can be used to address identification challenges.

Despite its strengths, few researchers have used Bockstael's (1996) approach since her paper was published. This may be due to the requirement for extensive spatial data on land use, land sales, and parcel attributes. Over time, these data have become easier to obtain, so perhaps this approach will become more common. In one recent application, Bigelow et al. (2014) develop a panel data set of land values for parcels in developed, agricultural, and forest uses in the Willamette Valley of Oregon. They estimate hedonic models using the Hausman-Taylor estimator, which allows them to treat land-use regulations as endogenous. Models of transitions from agriculture and forest to developed use are then estimated with data from Land Cover Trends (Loveland et al. 2002), which provide repeated observations of high-resolution land cover maps over a 27-year period. The authors use these models to simulate the effects of different urban growth policies on the spatial pattern of land and water use.

3.3. Land Use

Under the econometric approach, the econometric model is used to simulate the effects of the policy on land use. If the model is estimated with aggregate data, then the simulations produce corresponding aggregate estimates of the land-use changes induced by the policy. For example, Wu & Segerson (1995) simulate the effects of changes in agricultural commodity programs on the county shares of land in different crops. They find that, across all counties in Wisconsin, a 2.3% reduction in the target price for corn reduces the acreage of corn and soybeans by 1%. Wu & Segerson assume that crop shares are constant in the absence of policy interventions (i.e., they adopt a static baseline). Stavins (1999) allows for a dynamic baseline in which county land-use shares continue to change due to the partial adjustment structure of the econometric model. Baseline land-use changes are subtracted from changes under the policy. The use of a dynamic baseline can have large effects on the results of the policy simulations if, for example, there are large baseline changes in the land use that is targeted by the policy.

If the econometric model is estimated with plot-level or spatially explicit data, the results of the policy simulation can be displayed as maps. In this case, the estimated econometric models provide a set of rules that govern fine-scale changes in land use. For example, Lewis & Plantinga (2007) estimate an econometric model of land-use transitions using plot-level data, which yielded functions of the form

$$P_{ijkt} = F(\mathbf{X}_{it}, \mathbf{Z}; \hat{\boldsymbol{\beta}}_{jk}), \quad (1)$$

where P_{ijkt} is the probability that plot i changes from use j to k during the period starting in time t , $\mathbf{X}_{it}$ is a vector of county average returns and plot-level land quality variables in time t , $\mathbf{Z}$ is a vector of per-acre subsidies that augment returns to forests, and $\hat{\boldsymbol{\beta}}_{jk}$ is a vector of estimated parameters specific to the j -to- k transition. By overlaying maps of initial land use, land quality, and county boundaries, Lewis & Plantinga define spatially distinct parcels that map to sets of transition probabilities as defined in Equation 1. A stochastic simulation is then performed to determine which parcels on the landscape remain in the same use and which ones change uses. This process produces a set of maps corresponding to different values of $\mathbf{Z}$.³ The same procedure is used with an econometric model estimated with spatially explicit data.

The optimization approach also uses initial land-use maps as an input and produces simulated land-use maps as outputs. Polasky et al. (2008) use a map of 8,000 parcels in the Willamette Basin of Oregon classified according to uses such as row-crop agriculture and managed forest. The optimization algorithm decides whether to keep each parcel in its current use, change it to another use, or allocate it to one of many conservation alternatives. Rabotyagov et al. (2014) study a watershed in Iowa and divide their study area into more than 16,000 parcels, which are roughly the size of agricultural fields. Data from a field-level survey are used to identify the crop rotations, tillage, and conservation practices. The optimization problem involves finding the least-cost placement of conservation practices to achieve given levels of ambient water quality. Newburn et al. (2006) use a GIS map for Sonoma County, California, that identifies parcels in residential, vineyard, and undeveloped uses. Additional GIS data are used to indicate whether parcels are within a conservation priority area for habitat, open space, and rangeland, which determines the benefits of conserving them. Early reserve site selection studies (e.g., Church et al. 1996, Polasky et al. 2001) do not explicitly account for land use. Rather, in these studies the landscape is partitioned into sites, and the problem is to decide which sites to include in a reserve network to maximize the number of species protected.

3.4. Biophysical Models

Four basic types of biophysical models have been used in integrated economic land-use analyses (Table 1). These models can be classified according to how they account for spatial heterogeneity on the landscape⁴ and whether the biophysical processes in the model are aspatial or spatial. A parcel-specific biophysical model can capture a high degree of spatial heterogeneity because land use and other attributes of the land that influence biophysical processes can vary at the scale of parcels. In contrast, other biophysical models are based on the characteristics of aggregate areas, such as counties. In this case, when land changes use, the biophysical processes for new lands

³To account for the stochastic nature of the transition probabilities in Equation 1, Lewis & Plantinga (2007) simulate a large number of landscapes for each value of $\mathbf{Z}$, each of which is consistent with the underlying transition rules.

⁴Only landscape-scale analyses are considered here. There are also integrated land-use and biophysical studies that analyze optimal management of a single site, such as a farm (e.g., Johnson et al. 1991).

Table 1 Classification of biophysical models used in integrated economic land-use analyses

		Spatial heterogeneity	
		Representative parcels	Parcel-specific model
Biophysical processes	Aspatial	Wu & Segerson (1995), Plantinga et al. (1999)	Butsic et al. (2010), Lawler et al. (2014)
	Spatial	Rabotyagov et al. (2010)	Nalle et al. (2004), Polasky et al. (2008)

depend on the average characteristics of land in the county. There are also intermediate cases in which the biophysical processes can depend on the full distribution of land attributes for the aggregate area. Biophysical models can be spatial, meaning that the processes represented in the model depend on the spatial arrangement of land use and other land attributes. An example would be a model of wildlife habitat in which the reproductive success of a given species depends on the connectivity of habitat patches. In an aspatial model, only the total amount of land in different uses influences biophysical variables.

Wu & Segerson (1995) examine the effects on groundwater quality of different cropping patterns using an aspatial, aggregate model. They determine the percentage of farmland in each Wisconsin county that, on the basis of soil characteristics and other factors, is vulnerable to groundwater contamination if polluting crops (e.g., corn) are selected. The area of land in polluting crops in each county is then multiplied by the vulnerable percentage to obtain the farmland area that has the potential to contribute to groundwater contamination. This approach is equivalent to assuming a representative parcel for each county that has the average vulnerability of farmland in the county as well as the average distribution of land uses. In an analysis of the costs of carbon sequestration in forests, Plantinga et al. (1999) compute a weighted average of carbon yields for different forest species using weights based on forest species composition within each county. The carbon sequestration rate for new forests is assumed to be the same as the county average rate. A parcel-specific model would link the characteristics of individual parcels (e.g., vulnerability to contamination or the dominant forest species) and chosen land uses to biophysical outcomes.

Plantinga & Wu (2003) use the distribution of land quality in each aggregate area to refine estimates of the environmental benefits of removing land from agricultural production. Environmental production functions relate pollution from agricultural chemicals to site characteristics, including a measure of land quality, and a land-use model predicts the total amount of cropland that is converted to forest in each area. By accounting for the distribution of land quality in each aggregate area and assuming that agricultural lands are converted in order of increasing land quality, the authors obtain a more precise estimate of pollution reductions. A similar approach is used in FASOM (Forest and Agricultural Sector Optimization Model), developed by Adams et al. (1996). The authors categorize forests within each region according to ownership, species, site productivity, management intensity, and age class. Furthermore, crop, pasture, and forest are assigned to a land class, which indicates the potential for conversion to and out of forest on the basis of land productivity and historical conversion patterns. This classification identifies, for example, which cropland and pasture acres are eligible for conversion to forest on the basis of information about regional distributions of land productivity. Finally, Jian et al. (2010) simulate yields for bioenergy crops for each $0.1^{\circ} \times 0.1^{\circ}$ grid cell in the United States using GIS data on biogeochemical variables. Yields are aggregated to the county scale and are combined with economic data to estimate break-even prices of producing bioenergy crops.

Although most biophysical models based on aggregate land areas are aspatial, Rabotyagov et al. (2010) makes use of a watershed-scale hydrology model (the Soil and Water Assessment

Tool) that accounts for spatial linkages among aggregate land units. Although each land unit has homogeneous land use and land attributes, streamflow and in-stream concentrations of water pollutants depend on the spatial arrangement of these land units in relation to the stream network.

Lawler et al. (2014) make fine-scale (100-m-pixel) land-use projections for the contiguous United States that account for parcel-level variation in land quality. On the basis of these projections, the authors estimate changes in the amount of habitat available for 194 terrestrial vertebrate species, such as amphibians and at-risk birds, using data on their geographic ranges and habitat associations. The biophysical model is aspatial in that the assessment of habitat availability does not depend on the size or spatial arrangement of patches. However, in contrast to aggregate modeling approaches, the authors are able to link parcel-level information on land use to fine-scale data on species' ranges and habitat requirements. Beaudry et al. (2013) use a similar approach to study habitat changes for 20 bird species in Wisconsin. However, these authors account for the spatial arrangement of habitat (e.g., the amount of edge between forests and agricultural fields) in determining its suitability for each species.

Nelson et al. (2008), Polasky et al. (2008), and Lewis et al. (2011) account for land use at the parcel scale and spatial processes that affect habitat quality. Land-use maps are generated using optimization or econometric methods and are then evaluated in terms of the likelihood that the landscape will sustain species in the future. The biophysical model accounts for species-habitat compatibility (i.e., what land uses the species can use for habitat), the amount of habitat needed to support a breeding pair, and the ability of the species to move between patches of habitat. Nalle et al. (2004) use a biophysical model to estimate population sizes of selected species given the characteristics and spatial arrangement of land management units. The model stochastically simulates movements across the landscape and the breeding behavior of individual animals.

3.5. Economic Optimization Models

As discussed above, many optimization studies seek to maximize a biophysical objective subject to constraints expressed in economic terms (e.g., a total budget for land conservation). The dual to the problem is also investigated so that the objective is to minimize costs of achieving a stated biophysical target. In sectoral optimization studies, the objective is to maximize the sum of consumer and producer surpluses, yielding the competitive market equilibrium. This problem may be constrained by biophysical targets.

The simplest optimization problems involve designating a reserve network to maximize the number of species protected. This problem, referred to as the maximal coverage location problem, was first studied by ecologists (e.g., Church et al. 1996). Given information on the geographic distribution of species, the problem is to choose sites to maximize total coverage of species subject to a constraint on the number of sites in the reserve network. Ando et al. (1998) recognize that this formulation of the problem implicitly assumes that the cost of acquiring land for the network is equal for each site. This approach can produce extremely costly solutions, as sites with large numbers of endangered species are often found in urban areas with high land rents (e.g., southern Florida and Los Angeles). Using US county data on the presence of endangered species and on average land costs, Ando et al. solve a budget-constrained version of the maximal coverage problem and find dramatically lower costs compared with costs under the site-constrained problem. For example, the cost of covering one-half of the species under the budget-constrained version is less than one-third the cost under the site-constrained approach.

A number of extensions of the reserve site selection problem have been pursued along economic and biophysical dimensions. Costello & Polasky (2004) and Newburn et al. (2006) solve a dynamic version of the problem that accounts for the possibility that sites will be unavailable in the

future as the result of land development. Costello & Polasky show that, given threats from development and per-period budget constraints, there are substantial gains to optimally sequencing site selection. Strange et al. (2006) further extend the dynamic problem by allowing for the possibility of species extinction. Other authors examine how the solution changes when site attributes that affect habitat quality are incorporated (e.g., Fischer & Church 2003, Onal & Briers 2003). In the analysis by Fischer & Church (2003), sites with large perimeters are penalized, leading to the selection of sites with greater compactness and contiguity. Recent studies seek to directly optimize outcomes for species, often accounting for complex relationships between the spatial pattern of habitat and species survival (e.g., Nicholson et al. 2006, Polasky et al. 2008).

The increase in the economic and biophysical complexity of optimization problems has made it challenging for researchers to find explicit solutions. When the parcel-level benefits and costs are independent of one another, the optimal solution is easily obtained. Bateman et al. (2013) evaluate the effects of six land-use change scenarios on a range of ecosystem services, each of which is associated with a separate policy and regulatory regime. Changes in market and nonmarket services are measured on a 2-km scale. Bateman et al. then consider how the outcomes could be improved through the use of spatially differentiated policies. For example, to maximize the monetary value of ecosystem services, they choose the policy for each grid cell from among the six alternatives that produces the highest monetary value.

The problem can be much harder to solve when the benefits and costs are spatially and temporally dependent. For example, in Rabotyagov et al. (2010), nutrient loadings at the watershed outlet depend on the landscape-scale pattern of agricultural land use and on the hydrology of the system. The solution to the problem of achieving least-cost reductions in nutrient loadings must account for interdependencies among conservation activities adopted at many locations. Increasing the complexity of the problem are a large number of possible conservation practices and a multicriteria objective. Rabotyagov et al. use evolutionary algorithms to search for a cost-effective solution. Candidate solutions are subjected to mechanisms motivated by optimization processes observed in nature (e.g., selection, recombination, reproduction, and mutation) to produce new solutions that are evaluated with respect to the problem's objectives (Simon 2013). Heuristic algorithms are also applied in Nalle et al. (2004) and Polasky et al. (2008) to address challenges arising from large numbers of land parcels and choice variables as well as nonlinear and spatially dependent biophysical relationships. Although these algorithms can overcome computational limitations, they cannot guarantee optimality.

3.6. Economic Measures of Environmental Outcomes

Many econometric analyses evaluate specific policies. In some cases, the outcome of the policy is simply reported as the induced change in biophysical variables. For example, Wu & Segerson (1995) report changes in high-polluting acreage associated with a specified reduction in the target price for corn. Lewis et al. (2011) report changes in a biological score for different cost levels, where the costs are computed as the opportunity cost of the land in intensive agricultural uses. If the policy is a per-acre incentive for increasing land in a desired use, the incentive can be varied to trace out the marginal costs of changes in the biophysical variable. Lubowski et al. (2006a) simulate a combined subsidy and tax policy for increasing forest area. For each increment in the incentive, they calculate the change in total costs, measured as opportunity costs of the land in nonforest uses, the change in forest area, and the corresponding change in carbon stored in the forest. The ratio of the change in total cost to the associated change in carbon gives the marginal cost at the level of the incentive. A marginal cost curve for carbon is constructed by arraying marginal costs against cumulative carbon sequestration (Figure 2). Montgomery et al. (1994) use a sectoral optimization model to

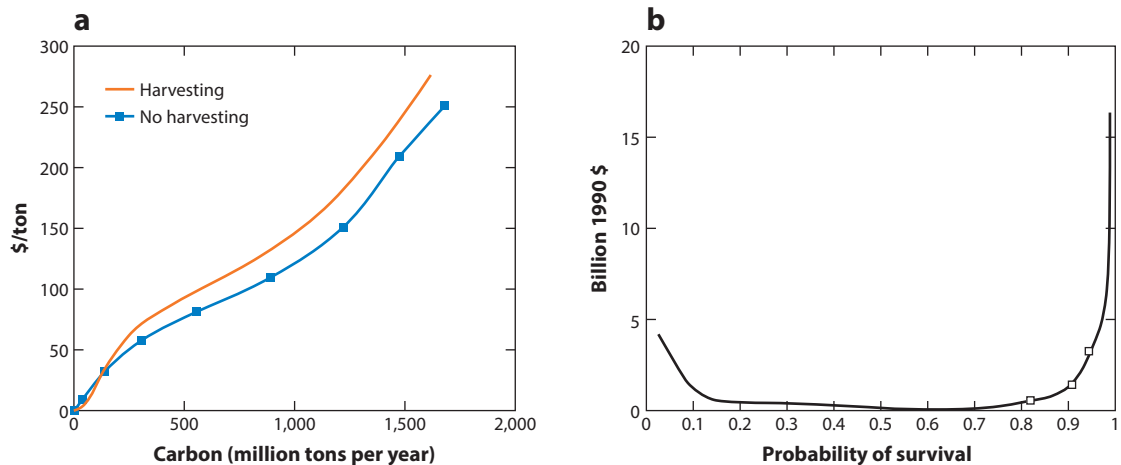


Figure 2

(a) Marginal costs of increasing carbon in forests. From Lubowski et al. (2006a) with permission. (b) Survival probability for the northern spotted owl. From Montgomery et al. (1994) with permission.

estimate a marginal cost curve for survival of the northern spotted owl (Figure 2). The costs of setting aside habitat for owls are measured in terms of forgone surplus from timber production.

When the outputs of a policy simulation are maps, researchers typically need to summarize large amounts of information (Plantinga & Lewis 2014). Lewis & Plantinga (2007) investigate the effects of a per-acre afforestation subsidy on forest fragmentation in South Carolina. For each value of the subsidy, they simulate 500 landscapes. As discussed above, each landscape is consistent with the underlying stochastic rules governing land-use transitions. To summarize the features of each landscape, the FRAGSTATS software program (McGarigal et al. 2012) is used to compute landscape metrics, including the percentage of the landscape in core forest (i.e., a forest patch that is more than a specified distance from the nearest nonforest edge) and the mean forest patch size. Lewis & Plantinga use this information to construct distributions for the landscape metrics and different levels of the subsidy. As Figure 3 shows, a \$25-per-acre subsidy shifts the core forest distribution to the right relative to a baseline with no subsidy. Lewis et al. (2011) use a similar approach to compute distributions over a biological score for different policies and cost levels.

The study of Bateman et al. (2013) differs from most other studies in this literature in that it estimates monetary values for nonmarket benefits associated with land-use policies, as opposed to just measuring the physical change in an environmental outcome. In particular, these authors report monetized changes in carbon emissions, outdoor recreation, and urban greenspace. The outdoor recreation analysis makes use of a trip generation function that estimates the number of trips from each location, given characteristics of the population at the location and travel time to and attributes of destination sites. The number, location, and characteristics of these destination sites, and thus the number of visits to them, vary under different land-use policies. The value of visits is estimated using results from a trip valuation meta-analysis. Bateman et al. present maps showing changes in the values of these nonmarket goods under alternative policy scenarios.

The results from optimization models are often presented as efficiency frontiers. For example, Polasky et al. (2008) maximize an aggregate biodiversity score subject to a constraint on the total value of land in the study area. By varying the constraint, they trace out an efficiency frontier between biodiversity score and total land value. In an interesting comparison, the authors show

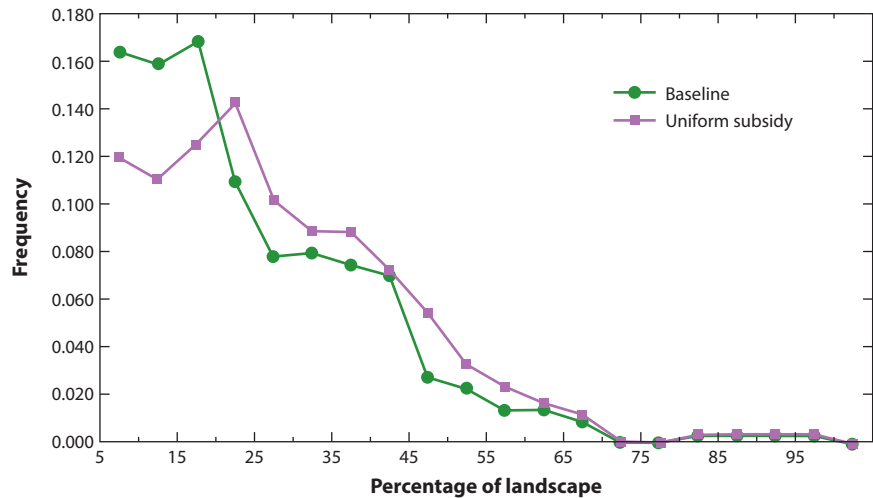


Figure 3

The effect of an afforestation subsidy on the core forest distribution. From Lewis & Plantinga (2007) with permission.

that the current landscape lies well within the efficiency frontier. Rabotyagov et al. (2010) solve a multiobjective optimization problem, which yields a three-dimensional frontier. **Figure 4** shows the estimated trade-offs between phosphorus and nitrogen loadings and costs of agricultural practices. These analyses identify the allocation of land that achieves a given biophysical target in a cost-effective manner. The use of benefits estimates, as in Bateman et al. (2013), can identify the allocation that maximizes net benefits. Although results such as these are especially useful, reliable benefits estimates are not always available or are difficult to obtain, especially in the case of nonuse values (Bateman et al. 2013).

4. DISCUSSION

This article reviews the growing literature in resource economics that involves the integration of economic land-use and biophysical models. Many biophysical models include sophisticated representations of biological and physical processes but exclude human influences on the system or treat them in a cursory way. However, economists are surely guilty at times of giving insufficient attention to important interactions of human systems with the natural environment. Integration of economic land-use models with biophysical models allows for a more comprehensive analysis of the human and natural systems. Biophysical models (of terrestrial systems) typically contain a GIS-based representation of the landscape, providing a direct linkage to economic models of land-use decisions.

This review demonstrates the progress that resource economists have made in incorporating biophysical models into their analyses. In early studies, aggregate changes in land use were typically converted into proportional changes in biophysical variables. For example, changes in bird abundance in Matthews et al. (2002) are proportional to county-level changes in forest and agricultural land. More recent analyses have integrated fine-scale land-use models with biophysical models that account for complex spatial processes. Such integration has allowed for more in-depth economic analyses of environmental problems such as Gulf of Mexico hypoxia

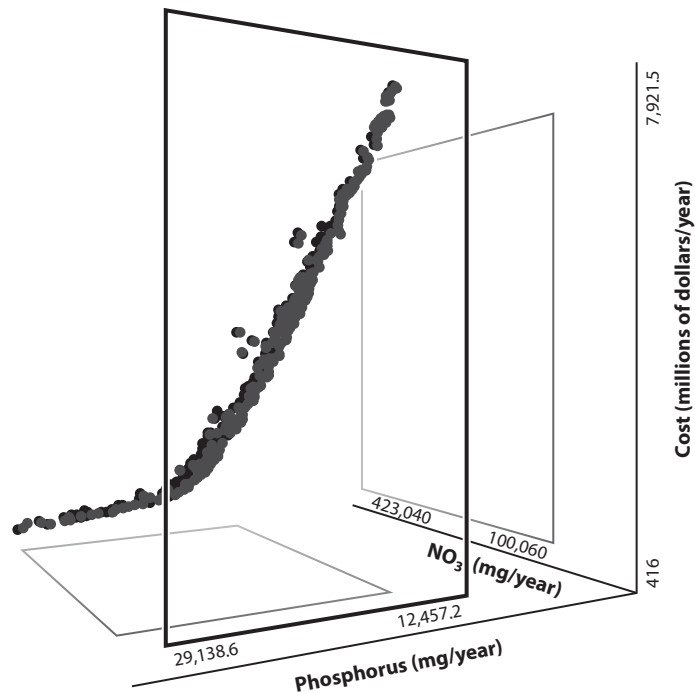


Figure 4

Efficiency frontier for phosphorus, NO_3 , and costs. From Rabotyagov et al. (2010) with permission.

(Rabotyagov et al. 2010), biodiversity loss (Polasky et al. 2008), and ecosystem service provision (Bateman et al. 2013). An important question, however, is whether the complexity of economic and biophysical models has appreciable effects on policy recommendations (Nelson et al. 2008). If simple models provide the same insights, then researchers need not expend time and effort on more sophisticated approaches. Nelson et al. (2008) conduct an analysis of trade-offs between species conservation and carbon sequestration using both simple and complex models. They find that greater model complexity did not have a large effect on modeling results or policy advice, although they acknowledge that differences in model assumptions and output metrics made comparisons difficult. Additional analyses are needed to determine whether complex modeling efforts are warranted.

For the most part, the studies reviewed here use either an econometric or an optimization approach. The advantage of optimization is that it identifies land-use patterns that efficiently achieve given biophysical goals. This approach provides crucial information to policy makers about trade-offs among competing objectives or, in the best of circumstances, cases in which goals are complementary (e.g., Nalle et al. 2004). The shortcoming of optimization studies is that they usually say little about how to achieve efficient solutions in practice. Reserve site selection studies, for example, often assume that inducing private landowners to add their land to a reserve network simply requires compensating them for the average rent in the area. The results of a landowner survey by van Kooten et al. (2002) suggest significant transactions costs associated with policies designed to convert agricultural land to forest.

Because they are estimated with observational data, econometric land-use models reflect how landowners have actually responded to the incentives they face in markets. As such, econometric

studies have the potential to measure more accurately how landowners will respond to land-use policies. Or, put differently, the models may implicitly capture the influence of factors that affect landowner decision making in practice but that are difficult to represent explicitly in optimization studies (Stavins 1999). Comparisons of studies on the costs of carbon sequestration in forests find that econometric-based estimates are generally higher than those produced in optimization studies (Dempsey et al. 2010). The findings from the carbon sequestration literature suggest that optimization studies provide a lower bound on the costs of policy-induced changes in environmental variables. A second advantage of econometric models is that they allow the researcher to represent asymmetric information between government agencies and landowners. For example, a landowner's willingness to accept a payment for converting her land to an alternative use is private information that the landowner has a disincentive to share with the conservation agency implementing the policy. In contrast to optimization studies that assume common knowledge about landowner opportunity costs, econometric land-use models can be used to explicitly model information asymmetries (Lewis et al. 2011, Mason & Plantinga 2013).

Fortunately, the econometric and optimization approaches are not mutually exclusive. Nelson et al. (2008) and Lewis et al. (2011) simulate land-use policies using an econometric approach and then, with the same basic data, use optimization to estimate efficiency frontiers. They evaluate the performance of different land-use policies in achieving biophysical goals, finding that in most such cases a small percentage of the efficient outcome is achieved. The difference is largely due to asymmetric information about willingness to accept, which prevents perfect targeting of incentives for land conversion. Bateman et al. (2013) also combine econometric and optimization approaches. Econometric models are used in policy simulations, and then optimization is used to determine the optimal spatial targeting of alternative policies. Additional research is needed to bridge the gap between efficient land-use patterns and what can be achieved with tractable, politically acceptable policies. Integrated economic land-use and biophysical models that combine econometric and optimization approaches can help achieve this goal.

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