Predicting Future Forestland Area: A Comparison of Econometric Approaches

SoEun Ahn, Andrew J. Plantinga, and Ralph J. Alig

ABSTRACT. Predictions of future forestland area are an important component of forest policy analyses. In this article, we test the ability of econometric land use models to accurately forecast forest area. We construct a panel data set for Alabama consisting of county and time-series observation for the period 1964 to 1992. We estimate models using restricted data sets—namely, data from early periods—and use out-of-sample values of dependent and independent variables to construct precise tests of the model's forecasting accuracy. Three model specifications are examined: ordinary least squares, dummy variables (fixed effects), and error components (random effects). We find that the dummy variables model produces more accurate forecasts at the county and state level than the other model specifications. This result is related to the ability of the dummy variables model to more completely control for cross-sectional variation in the dependent variables. This suggests that the estimated model parameters better capture the temporal relationship between forest area and economic variables. For. Sci. 46(3):363–376.

Additional Key Words: Forest area, econometric analysis, forecasting, land rent.

THE SIZE OF THE FORESTLAND BASE plays a critical role in determining the quantity and quality of outputs from the forest. Forestland area influences the volume of available timber and, thus, affects timber supply decisions and, ultimately, timber prices. In addition, the production of noncommodity forest outputs such as wildlife habitat is closely linked to the area and distribution of forests. Accurate evaluation of prospective forest policies requires an understanding of the underlying patterns of forest area change and estimates of a policy's impact on future forest area. In recent decades, analysts have increasingly used econometric methods to model and forecast forest area (e.g., Alig 1986, Parks and Murray 1994, Mauldin et al. 1999). The basic approach is to estimate the relationship between the area of land in alternative uses (forest, cropland, etc.) and key determinants influencing land use decisions (e.g., the net economic returns to land in different uses). Given projections of the land use determinants, the fitted econometric models are used to generate predictions of future forest area. This approach has been used in the Resources Planning Act (RPA) assessments conducted by the Forest Service (e.g., USDA Forest Service 1990) and in analyses of forested wetlands depletion (Stavins and Jaffe 1990) and preservation (Parks and Kramer 1995), soil erosion control (Plantinga 1996), and carbon sequestration (Plantinga et al. 1999, Stavins 1999).

The purpose of this article is to investigate the accuracy of forest area projections. Given the importance of area projections for forest policy analysis, a key question is whether econometric land use models can accurately predict the future. Our strategy is to estimate models with a restricted data set—namely, data from early periods—and predict observations from later periods. Since we observe out-of-

SoEun Ahn is Research Associate, Department of Resource Economics and Policy, University of Maine, Orono, ME 04469-5782—Phone: (207) 581-3172; E-mail: Soeun_Ahn@umit.maine.edu. Andrew J. Plantinga is Assistant Professor, Department of Resource Economics and Policy, University of Maine, Orono, ME 04469-5782—Phone: (207) 581–3156; E-mail: andrewp@maine.maine.edu; Fax: (207) 581-4278. Ralph J. Alig is Research Forester, USDA Forest Service, Pacific Northwest Research Station, 3200 Jefferson Way, Corvallis, OR 97331—Phone: (541) 294-5438; E-mail: Alig_Ralph/r6pnw_corvallis@fs.fed.us.

Acknowledgments: S. Ahn and A. Plantinga share senior authorship. The authors acknowledge helpful comments and suggestions from *Forest Science* Editor Robert Haight, an Associate Editor, and three anonymous referees. Financial support for this research was provided through a Cooperative Agreement between the USDA Forest Service, Pacific Northwest Station, and the University of Maine. Maine Agricultural and Forest Experiment Station Publication No. 2384.

Manuscript received March 15, 1999. Accepted December 6, 1999.

sample values of the dependent and independent variables, we can construct a precise test of the model's predictive ability. The forecasting accuracy of econometric land use models is also a timely issue. During the past decade, there have been significant improvements in the methodology used to model land use, and the new generation of land use models appear to have a number of advantages over models developed during the 1980s. However, as discussed in the next section, there are reasons why econometric land use models, despite recent improvements, may not be able to forecast forest area accurately. In this article, we test the predictive ability of the new generation of land use models and explore alternative model specifications that may improve forecasting accuracy.

In subsequent sections, we present a dynamic model of the landowner's optimal allocation problem and aggregate the optimal allocations to form an econometric model of land use shares that can be estimated with available aggregate data. We estimate three versions of the land use model using data on Alabama covering the period 1964 to 1992. Ordinary least squares, dummy variable (fixed effects), and error components (random effects) models are evaluated. The set of models are then estimated with restricted data sets for the periods 1964 to 1982 and 1964 to 1974. With these models, we generate out-of-sample forecasts of forest area in subsequent periods using the sets of observed explanatory variables. For the three model specifications, we compare the predicted values to the observed values and develop quantitative measures of the overall accuracy of the forecasts.

The Challenge of Predicting Future Forest Area

Most previous land use analyses employ aggregate (e.g., county) data. Typically, forest area observations are from Forest Inventory and Analysis (FIA) surveys conducted by the Forest Service and agricultural land area data are from the Census of Agriculture.[1] Urban and other uses are commonly treated as a residual category. FIA inventories are conducted on a state-by-state basis and on 8 to 15 yr cycles and, for most states, three or four inventories have been completed. Thus, a data panel can be constructed for a state consisting of time-series and cross-sectional (county) observations. Since only a few inventories are available, panels are limited in the temporal dimension; however, panels tend to be rich in the cross-sectional dimension since most states have many counties (the average is about 60 per state).

In the typical application, researchers pool time-series and cross-sectional observations and estimate a single set of parameters for a state or group of states. Since the cross-sectional observations are combined, it is necessary to control for all relevant factors that vary across counties. In retrospect, the analyses conducted during the 1980s omit a critical factor—land quality. Later studies by Lichtenberg (1989) and Stavins and Jaffe (1990) demonstrate that aggregate land use allocations are strongly dependent on the characteristics of land within a county. As noted by Hardie and Parks (1997), aggregate data models that ignore heterogeneous land quality may suffer from specification error, which can bias parameter estimates such as those on net returns measures. The omission of land quality variables can potentially explain the mixed results of analyses conducted during the 1980s. In many of these studies, estimates of key parameters have unexpected signs or are not significantly different from zero, and the explanatory power of models is often low.

Recent analyses that control for heterogeneous land quality tend to produce better results (Parks and Murray 1994, Wu and Segerson 1995, Plantinga 1996, Hardie and Parks 1997, Plantinga et al. 1999, Mauldin et al. 1999). Nevertheless, it is unclear that the new generation of models will produce accurate forecasts of forest area. The central issues are the structure of the data used to estimate the models and the dynamic nature of the forestland allocation decision. As noted above, the available data sets provide many cross-sectional but few time-series observations and, thus, most of the observed variation in land use is spatial (across county) variation. However, forecasting involves prediction in the temporal dimension and, for this purpose, we need to quantify how forest area has responded over time to different levels of the explanatory variables. The challenge is to adequately control for differences across counties so that the limited information on forest area over time can be used to estimate the temporal relationships of interest.

Our focus in this paper is on the prediction of future forest area because it presents a particular challenge for land use models estimated with cross-sectional data.[2] The decision to allocate land to forest is a fundamentally dynamic process.[3] Forestry requires a long-term commitment of land that is difficult and costly to reverse, and the long-term nature of the investment increases uncertainty about future returns. Schatzki (1998) demonstrates in a theoretical framework that option values arise in connection to decisions to convert agricultural land to forest. In this context, the option value is the additional value of keeping the land in agriculture and avoiding an irreversible and potentially uneconomical conversion decision. In an empirical study of the Conservation Reserve Program, Schatzki finds some evidence that landowners take account of option values in deciding whether or not to convert land to forest. Option values arise in the context of dynamic decision-making and illustrate the dynamic nature of forest-

[1] Readers may wonder why land use modelers do not take advantage of the detailed plot-level information provided by FIA inventories. The reason is that the FIA inventories do not provide sufficient information on nonforest uses. Consequently, researchers must combine aggregate (county) data on agricultural uses from the Census of Agriculture with corresponding county data from the FIA.

[2] Nerlove (1971) points out that many applications in economics involve panel data with a large number of cross-sectional observations but only a few time-series observations. Nerlove (1971) and Balestra and Nerlove (1966) examine different approaches to modeling autoregressive processes using data with these characteristics.

[3] In contrast, agricultural land use decisions—e.g., a farmer's decision to grow row or field crops—can be reasonably viewed as a static process provided that changes in land use do not involve large capital investments. Within a single period, landowners observe current economic variables and allocate their land based on expected returns to alternative uses.

land allocation decisions. Since time-series data are required to model dynamic processes, the question is whether or not a land use model estimated with limited temporal data can adequately represent the dynamic process governing forest-land allocation decisions.

We explore this issue by testing the model's ability to predict future forest area. Three model specifications are examined. The first model is estimated with pooled data and is typical of models estimated in earlier studies. This model includes variables to control for cross-sectional variation in land quality. The next two models include cross-sectional dummy variables and error components. Nerlove (1971) explains how these models can be used to estimate dynamic relationships with data sets containing many cross-sectional but few time-series observations. Dummy variables and error components control for unexplained cross-sectional variation and, in principle, ensure that the model measures the temporal relationship between the dependent and independent variables. Since the pooled model is a restricted form of the dummy variables and error components models, we can conduct hypothesis tests to determine if the set of explanatory variables adequately controls for cross-sectional variation.

The Landowner's Allocation Problem

In this section, we present a model of the landowner's problem of allocating a fixed amount of land to alternative uses.[4] The solution to the landowner's optimization problem yields an expression for the maximum discounted profits from each parcel of land. The profit expressions are incorporated into a second optimization problem that solves for the optimal shares of total land allocated to each use. In the following section, the optimal share equations are aggregated to yield an econometric model that can be estimated with available data.

We assume that a price-taking risk-neutral landowner maximizes discounted expected net returns by allocating a 1 ha parcel of land to alternative uses. For simplicity, we limit the landowner's choice to two uses—forestry and agriculture—though the model can be easily extended to include additional or more refined land use categories. In addition, we assume that the parcel has uniform quality and that trees are even-aged. The landowner maximizes the present discounted value of expected net returns

$$\max_{\{u_t\},\{v_t\}} \sum_{t=0}^{T} \delta^t [R_t^f(a_t)v_t + R_t^a \cdot (1-u_t)v_t] + \delta^{T+1} V_{T+1}(a_{T+1}) \quad (1)$$

subject to

$$u_t = \{0,1\}; v_t = \{0,1\}; a_{t+1} = a_t u_t (1-v_t) + u_t; a_t \geq 0; R_t^f(0) = 0$$

and a_0 given. Note that we do not attempt to model option values explicitly, either here or in the specification of the empirical models in the following section. The data are unavailable for this purpose, and techniques for incorporating the implications of option value theory into econometric models are in their infancy (see Dixit and Pindyck 1994 for a review of empirical studies and Schatzki 1998 for an application to land use). As noted below, the effects of option values will be captured, to some extent, in the coefficients on the forest rent variables in our empirical models.

At the start of period t, the landowner decides whether to harvest ($v_t = 1$) or continue to grow ($v_t = 0$) an existing stand and whether to allocate the parcel to forestry ($u_t = 1$) or agriculture ($u_t = 0$) during the period. The age of the stand (in years) at the start of period t is denoted a_t. Over time, the stand age is determined by harvesting and land use decisions according to the equation of motion. The expected net returns from harvesting a stand of age a_t in period t are $R_t^f(a_t)$ and the expected net returns to agriculture in period t are R_t^a. The land must be cleared of trees at the start of a period ($v_t = 1$) in order for agricultural crops to be grown and net returns realized. Land conversion costs are assumed to be included in the net returns measures. Lastly, δ is a constant discount factor and $V_{T+1}(a_{T+1})$ is the expected salvage value.

The solution to (1) is given by Bellman's equation

$$V_t(a_t) = \max_{u_t, v_t} [R_t^f(a_t)v_t + R_t^a \cdot (1-u_t)v_t + \delta V_{t+1}(a_{t+1})] \quad (2)$$

for $t = 0,1,\ldots,T$ and subject to the above constraints. $V_t(a_t)$ is interpreted as the value of the optimally managed land parcel. Since the right-hand side of (2) is linear in the control u_t, the solution involves the choice of either forestry or agriculture each period. In period t, this decision depends on the relative magnitude of W_t^f and W_t^a, defined as

$$\begin{aligned} W_t^f &= R_t^f(a_t)v_t^* + \delta V_{t+1}[a_t(1-v_t^*)+1] \\ W_t^a &= R_t^f(a_t) + R_t^a + \delta V_{t+1}(0) \end{aligned} \quad (3)$$

where v_t^* is the optimal harvesting decision and $V_t(0)$ is the bareland value. The landowner allocates the parcel to forestry in time t if $W_t^f \geq W_t^a$ and to agriculture if $W_t^a > W_t^f$.

Plantinga (1996) shows that under certain conditions the allocation decision reduces to a simple comparison of the present discounted value of net returns to each use. Specifically, if landowners have static expectations regarding future net returns (i.e., $R_s^f(a_s) = R^f(t,a)$ and $R_s^a = R^a(t)$ for $s = t, t+1, \ldots, T$), the land is initially bare ($a_t = 0$), and the time horizon is infinitely long ($T = \infty$), the expressions for W_t^f and W_t^a become

$$\begin{aligned} W^f(t) &= \frac{\delta^{a^*}}{1-\delta^{a^*}} R^f(t,a^*) \\ W^a(t) &= \frac{1}{1-\delta} R^a(t) \end{aligned} \quad (4)$$

where a^* is the optimal rotation age given the net returns $R^f(t,a)$. The first equation in (4) is the familiar expression for the present value of an infinite series of Faustmann rotations or, alternatively, the maximized value of bareland allocated to forest. The second equation is the present value of an infinite series of annual crop rotations or the maximized

[4] This formulation of the problem is based on Plantinga (1996) and Miller and Plantinga (1999).

value of bareland allocated to agriculture. As in previous studies, we focus on this solution to the landowner's allocation problem because it conforms to the data available for measuring the net returns to forestry and agriculture.

As noted above, we assume that each land parcel has uniform quality. In the context of our model, land quality influences the net returns to forestry and agriculture and, thus, to distinguish between parcels of varying quality, we introduce the index j ($j = 1, \ldots, J$) to the net returns measures in (4), where J is the number of land quality classes. Also, we might expect the skills and knowledge possessed by individual landowners to influence net returns. For landowner $n_i (n_i = 1, \ldots, N_i)$ in county i ($i = 1, \ldots, I$), where N_i is the number of landowners in county i and I is the number of counties, (4) becomes

$$\begin{aligned} W_j^f(t,n_i) &= \frac{\delta^{a^*}}{1-\delta^{a^*}} R^f(t,n_i,a^*) \\ W_j^a(t,n_i) &= \frac{1}{1-\delta} R^a(t,n_i) \end{aligned} \tag{5}$$

Given the landowner's objective of profit maximization, the net returns to landowner n_i from a parcel of quality j can be expressed

$$W_j(t,n_i) = \max\{W_j^f(t,n_i,a^*), W_j^a(t,n_i)\}.$$

Suppose that landowner n_i holds $H_j(t, n_i)$ ha of quality j land in time t. To maximize total profits from the land, the landowner selects the area of land $h_{jk}(t, n_i) \geq 0$ to allocate to forestry ($k = 1$) and agriculture ($k = 2$) in period t to maximize

$$\sum_k W_j(t,n_i) h_{jk}(t,n_i) \tag{6}$$

subject to

$$\sum_k h_{jk}(t,n_i) = H_j(t,n_i)$$

The Kuhn-Tucker solution to (6) is the optimal allocation

$$h_{jk}^*(W_j(t,n_i),n_i) = \{0, H_j(t,n_i)\},$$

indicating that all land of quality j is allocated to either forestry or agriculture. The optimal share of the landowner's total land,

$$H(t,n_i) = \sum_{j=1}^{J} H_j(t,n_i),$$

allocated to use k is

$$f_k(\mathbf{X}(t,n_i),n_i) = \frac{1}{H(t,n_i)} \sum_{j=1}^{J} h_{jk}^*(W_j(t,n_i),n_i) \tag{7}$$

The optimal shares are confined to the unit interval and are determined implicitly by land quality factors embedded in the net returns functions. Thus, we define $\mathbf{X}(t, n_i)$ as a vector of decision variables that includes the J functions $W_j(t, n_i)$ and composite measures of land quality.

An Econometric Model of Aggregate Land Use Shares

The optimal land use shares for individual landowners, $f_k(\mathbf{X}(t, n_i), n_i)$, must be aggregated to the county level to be conformable with the available data.[5] We begin by recognizing that, in practice, that optimal shares may differ from actual shares due to exogenous shocks that occur after the land use decision is made. For instance, the *ex post* optimal share of forestland may be lower than the actual share if there are poor growing conditions or pest infestations. The actual share of land allocated to use k by owner n_i is

$$s_k(t,n_i) = f_k(\mathbf{X}(t,n_i),n_i) + \gamma_k(t,n_i) \tag{8}$$

where the $\gamma_k(t, n_i)$ are mean zero disturbances and, given that the actual and optimal shares sum to 1,

$$\sum_k \gamma_k(t,n_i) = 0$$

Given the exogenous nature of the shocks, we assume they are uncorrelated with the decision variables:

$$E[X_h(t,n_i)\gamma_k(t,n_i)] = 0 \text{ for all } t, n_i, h, \text{ and } k.$$

Aggregate measures of forest and agricultural land areas are compiled from area-frame surveys of individual allocation decisions and self-enumerated reports, respectively. The observed share of land allocated to use k in county i, $0 \leq y_k(t, i) \leq 1$, may be assembled as

$$\begin{aligned} y_k(t,i) &= \sum_{n_i=1}^{N_i} w(t,n_i)[s_k(t,n_i) + \phi_k(t,n_i)] + \bar{\phi}_k(t) \\ &= p_k(t,i) + \varepsilon_k(t,i) \end{aligned} \tag{9}$$

If the data are based on an area-frame sample, $w(t, n_i)$ represents the sample weight assigned to individual n_i, $\phi_k(t, n_i)$ is the potential sampling error associated with each observation, and $\bar{\phi}_k(t)$ is the aggregate sampling error. When the data are derived from a complete enumeration of the population, $w(t, n_i)$ is relative share of land in county i held by landowner n_i, and the error terms have a corresponding interpretation. We assume that the sampling errors have zero mean, are uncorrelated across time, counties, and individuals but are correlated across uses (by construction), and are uncorrelated with the decision variables.

We interpret $p_k(t, i)$ as the expected share of land in county i allocated to use k at time t. By substituting (8) into (9), we see that the expected shares are a function of the full set of decision variables, $\mathbf{X}(t, n_i)$for all n_i. As with the land share data, individual-specific information on the decision variables is typically unavailable, and researchers commonly use county-level averages. The county data is denoted $\mathbf{X}(t, i)$ and

[5] The material in this section is based on Miller and Plantinga (1999).

include proxy variables for the land quality characteristics of county i. The composite error terms $\varepsilon_k(t, i)$ are assumed to have a mean-variance structure similar to the $\gamma_k(t, n_i)$. In particular, the county-level decision variables are assumed to be uncorrelated with the aggregate errors in the observed land use shares: $E[X_h(t,i)\varepsilon_k(t,i)] = 0$ for all t, i, h, k. To account for land in county i allocated to uses other than forestry and agriculture (e.g., urbanized land), we define the share of land in residual land uses as $p_3(t,i) = 1 - p_1(t,i) - p_2(t,i)$. We also augment $\mathbf{X}(t, i)$ to include variables that explain the allocation of land to these uses.

We follow earlier authors (Parks and Murray 1994, Wu and Segerson 1995, Hardie and Parks 1997, Plantinga et al. 1999, Mauldin et al. 1999) and specify the expected shares as a logistic function of the linear combination of decision variables and unknown parameters β_k,

$$p_k(t,i) = \frac{\exp(\beta_k' X(t,i))}{\sum_{k=1}^{3} \exp(\beta_k' X(t,i))} \tag{10}$$

The logistic specification is convenient because it constrains the shares to the unit interval and the transformation in Chapter 19 of Judge et al. (1988) yields a model linear in the parameters,

$$\ln(y_k(t,i) / y_1(t,i)) = \beta_k' X(t,i) - \beta_1' X(t,i) + \tilde{\varepsilon}_k, \tag{11}$$

where $\tilde{\varepsilon}_k$ is the resulting error term. The model is identified if we constrain $\beta_1 = 0$.

It is well known that the logarithmic transformation may induce heteroskedasticity in (9). In applications involving aggregated multinomial data, researchers often use the minimum chi-square procedure described by Maddala (1983) to correct for heteroskedasticity. This approach requires information on the number of trials for each individual or, in the present context, the number of parcels used to construct the sample proportions $y_k(i, t)$. We do not have this information on sample size and, in any event, it would differ by land use since our observations are taken from different sources. However, the model may exhibit heteroskedasticity of a more general form and, in the application presented below, we use White's (1980) estimate of the covariance matrix that allows for a general heteroskedastic structure.

An Application to Land Use in Alabama

We estimate the model in (11) using data on land use in Alabama. The forest share, denoted y_{1it}, is defined as the share of total land in each county in private timberland. Private timberland includes land held by industrial and nonindustrial owners and, in Alabama, approximately 75% is owned by the latter group. We exclude the small amount of forestland not meeting the timberland definition[6] because timber yields are relatively low on these lands, suggesting their use is determined by factors other than net returns. Public forestland is excluded for similar reasons. Observations on the 67 counties in Alabama are available from FIA inventories for 1963, 1972, 1982, and 1990. Statewide, approximately 65% of the land in Alabama is in private timberland. The agricultural share, y_{2it}, is defined as the share of land in cropland and pasture. County-level observations are available from the Census of Agriculture for 1964, 1969, 1974, 1978, 1982, 1987, and 1992. The statewide share in agricultural use is approximately 18%. The share of land in urban/other uses, y_{3it}, is defined as the share of total land in uses other than forestry and agriculture and includes developed land in urban, suburban, and rural areas, and other unclassified land. Total land area excludes land in public forests and parks since these uses of land are assumed to be exogenously determined.

Table 1. Absolute and percentage changes in agricultural land and private timberland area in Alabama, by census and inventory years.

Year	Agriculture*	% change	Private timber†	% change
1963			8,386	
1964	2,882			
1969	2,979	0.034		
1972			8,230	–0.018
1974	2,880	–0.033		
1978	2,739	–0.049		
1982	2,543	–0.072	8,328	0.012
1987	2,321	–0.087		
1990			8,412	0.010
1992	2,172	–0.064		

* Agricultural land area (in 1000 ha) is from Census of Agriculture.
† Private timber land area (in 1000 ha) is from Forestry Inventory and Analysis.

Since measurements of forest and agricultural land area are taken at different points in time, we must use interpolation with one of the data series to produce a consistent set of observations. We have chosen to interpolate forest area observations to match the available agricultural data because we believe that this will introduce less measurement error. By examining past inventories, we see that average annual changes in Alabama's agricultural land area have been greater—in absolute and percentage terms—than changes in forest area (Table 1). This suggests that agricultural land area will tend to fluctuate more than forest area between inventories and that interpolated forest area observations will be more accurate. Since our land use categories are exhaustive,

$$\Delta y_1(i,t) + \Delta y_2(i,t) + \Delta y_3(i,t) = 0,$$

where Δ signifies a change in the variable. Thus, if the decline in agricultural land area is greater than the increase in forest area, the increase in urban/other land area must make up the difference. If agricultural acreage increases by more than forest area declines, then urban/other land area must decrease. This is possible since the urban/other land category includes unclassified lands such as wetlands, which may be converted to agriculture.

Net returns from private timberland, denoted fr_{it}, are measured as the present discounted value of the infinite

[6] The FIA definition of timberland is forestland producing, or capable of producing, more than 20 ft^3/ac/yr of industrial wood crops under natural conditions, which is not withdrawn from timber utilization and not associated with urban or rural development.

stream of real timber revenues per acre.[7] We ignore timber management costs since intensively managed timberlands are a negligible portion of the private timberland base in the South (USDA Forest Service 1988, Dubois et al. 1997). Revenue streams are calculated separately for major forest types (planted pine, naturally regenerated pine, oak–pine, oak–hickory, and oak–gum–cypress) using type-specific timber yield curves, rotation lengths and stumpage prices. Yield curves are from Birdsey (1992), and rotation lengths correspond to the Faustmann rotation for a 5% discount rate. Revenue streams are also discounted using a 5% interest rate. Net returns for individual counties are calculated as a weighted average of type-specific net returns where weights are based on the forest type composition of counties.

Stumpage prices are from TimberMart South (TMS) for the period 1976–1992. TMS pine sawtimber prices are used for planted and natural pine stands, and TMS mixed hardwood prices are used for oak–pine, oak–hickory, and oak–gum–cypress stands. A stumpage price series for Louisiana (Howard 1997) is used to construct an Alabama series for the years prior to 1976.[8] We posit that landowners need to observe a sustained increase in net returns before committing their land to forest. Accordingly, landowners are assumed to consider the average price over the preceding 3 yr period in forming expectations of future prices. Due to data limitations, we have not modeled explicitly option values or nontimber benefits derived from the land; however, we note that the model coefficients account for these effects implicitly. For example, if there are significant option values associated with conversion of land to forest, landowners should be somewhat unresponsive to increases in the relative returns to forestry, and this should be reflected in a small coefficient on fr_{it}.

Agricultural net returns, ar_{it}, equal the real annual per-acre net revenues from crop and pasture land. By (5), ar_{it} is the proportional to the present discounted value of the infinite stream of annual crop revenues. Accordingly, the discounting term $1/(1-\delta)$ is embedded in the model parameters [β_{22} and β_{32} in Equations (12), (13), and (14)]. Net revenue for each county is a weighted average of revenue (price times yield) less variable production costs for major crop (cotton, soybean, and corn) and pasture uses where weights correspond to agricultural land shares within the county. Annual average crop prices are from the Alabama Agricultural Statistics Service and yield data for each county and crop are from the Census of Agriculture and USDA Economic Research Service (ERS). Variable production costs are the total variable cash expenditures per acre reported in regional crop budget reports by ERS. We assume that landowners base their expectations of future net returns on last period's net return.

Crop prices are defined as the prices received by farmers and, thus, they reflect the influence of price support programs such as nonrecourse loans by the Commodity Credit Corporation and government commodity purchases (see Hallberg 1992 for more details on U.S. farm policy). Our net returns measures do not, however, reflect the influence of income support programs such as deficiency payments or supply management programs such as acreage reduction programs. Unfortunately, the provisions of these programs are extremely detailed, tied to conditions at the farm level, and dependent on historical farm management decisions. Consequently, we are unable to precisely measure the effects of these programs on average net returns in a county, though we acknowledge that they affect the profitability of agriculture and, therefore, land allocation decisions.

In many empirical land use analyses, population measures are used to account for the allocation of land to nonrural uses (e.g., Wu and Segerson 1995, Hardie and Parks 1997). In this study, we use population density (total county population divided by total county land area), pd_{it}, to explain the share of land devoted to urban/other uses. Total population for each county is taken from Bureau of the Census reports, and linear interpolation is used to estimate population in years between censuses. We also include two land quality measures, the average Land Capability Class (LCC) rating, lq_{1i}, and the percentage of total land in LCC I and II, lq_{2i}. LCC ratings (USDA 1973) are derived from county-level soil surveys and based on twelve soil characteristics (e.g., slope, permeability). The rating for a land parcel ranges from I to VIII, where I is the most productive land and VIII is the least productive. Thus, a county with a higher value of lq_{1i} has lower quality land, on average. lq_{2i} is included to account for the presence of highly productive land suitable for intensive agricultural uses. lq_{1i} and lq_{2i} are not indexed by t since land quality measures remain essentially constant over time.

Estimation Results

We estimate three specifications of the model in (11) using three data sets. The first model is estimated with pooled data and specified

$$\begin{aligned}\ln(y_{2it}/y_{1it}) &= \beta_{20}+\beta_{21}fr_{it}+\beta_{22}ar_{it}+\beta_{23}pd_{it}\\&\quad+\beta_{24}lq_{1i}+\beta_{25}lq_{2i}+\mu_{2it}\\\ln(y_{3it}/y_{1it}) &= \beta_{30}+\beta_{31}fr_{it}+\beta_{32}ar_{it}+\beta_{33}pd_{it}\\&\quad+\beta_{34}lq_{1i}+\beta_{35}lq_{2i}+\mu_{3it}\end{aligned}\tag{12}$$

for all i and t, where $\mu_2 \sim (0, \Omega_2)$, $\mu_3 \sim (0, \Omega_3)$, and Ω_2 and Ω_3 are diagonal matrices. Equation (12) is estimated with ordinary least squares, and the procedure in White (1980) is used to form a consistent estimate of the covariance matrix for the estimated parameters. The model in (12), referred to as the OLS model, is typical of models estimated in earlier studies.

In the two additional specifications of (11), dummy variables (fixed effects) and error components (random effects) are included in (12). The dummy variables (or one-way fixed effects) model is specified

[7] Nominal net returns from forestry and agriculture are deflated using the Producer Price Index for all commodities (1982 = 100).

[8] Starting with the 1976 observations for Alabama, we construct a price series back to 1961 by assuming that annual percentage changes are the same as those in the Louisiana series over this period. Alabama and Louisiana prices track closely over the period 1976 to 1992.

$$\ln(y_{2it} / y_{1it}) = \beta_{21} fr_{it} + \beta_{22} ar_{it} + \beta_{23} pd_{it} + \alpha_{2i} + \mu_{2it}$$

$$\ln(y_{3it} / y_{1it}) = \beta_{31} fr_{it} + \beta_{32} ar_{it} + \beta_{33} pd_{it} + \alpha_{3i} + \mu_{3it} \quad (13)$$

for all i and t. We assume $\mu_2 \sim (0, \sigma_2^2 M)$ and $\mu_3 \sim (0, \sigma_3^2 M)$, where M is the identity matrix.[9] Compared to (12), the model in (13) includes a dummy variable parameter (or intercept term) for each of the 67 counties in the data set (α_{2i} and α_{3i}, where $i = 1, \ldots, 67$). The intercept terms (β_{20} and β_{30}) and land quality variables (lq_{1i} and lq_{2i}) must be dropped from (13) to avoid perfect collinearity with the county dummy variables.

The dummy variables specification may be warranted if there are known or hypothesized structural differences across sample points.[10] In the present context, there may be systematic differences across counties in physiographic characteristics (e.g., soil quality, climate) or landowner objectives related, for instance, to nonmarket amenities. The dummy variables control for differences across counties that are not measured by the other explanatory variables in the model. Relative to the dummy variables model, the OLS model imposes the restriction $\alpha_{2i} = \alpha_{3i} = 0$ for all i. By testing these restrictions, we can determine if the explanatory variables in the OLS model adequately measure the cross-sectional variation in the dependent variables.

The third alternative considered is the error components model, specified as

$$\ln(y_{2it} / y_{1it}) = \beta_{20} + \beta_{21} fr_{it} + \beta_{22} ar_{it} + \beta_{23} pd_{it} + \beta_{24} lq_{1i} + \beta_{25} lq_{2i} + \alpha_{2i} + \mu_{2it}$$

$$\ln(y_{3it} / y_{1it}) = \beta_{30} + \beta_{31} fr_{it} + \beta_{32} ar_{it} + \beta_{33} pd_{it} + \beta_{34} lq_{1i} + \beta_{35} lq_{2i} + \alpha_{3i} + \mu_{3it} \quad (14)$$

for all i and t. The error components are assumed to have the following properties:

$$E[\alpha_{2i}] = E[\alpha_{3i}] = 0;$$
$$E[\alpha_{2i}^2] = \sigma_{\alpha_2}^2, E[\alpha_{3i}^2] = \sigma_{\alpha_3}^2;$$
$$E[\alpha_{2i}\alpha_{2j}] = E[\alpha_{3i}\alpha_{3j}] = 0$$

for $i \neq j$, and α_{2i} and μ_{2it} and α_{3i} and μ_{3it} are uncorrelated for all i and t. The specification is similar to (13) except that α_{2i} and α_{3i} are interpreted as random variables rather than fixed parameters. With respect to this application, the error components model would be used if the unmeasured differences across counties are random disturbances (e.g., county-specific weather shocks). In contrast to the dummy variables model that requires the estimation of many additional parameters, only the variance of the error components distribution needs to be estimated. However, the error components model is clearly more restrictive than the dummy variables model which imposes no distributional assumptions on α_{2i} and α_{3i}.

We begin by estimating the set of three models with the full data set covering the period 1964 to 1992 (Table 2). For the OLS model, the estimated coefficients have the expected signs and the key parameter estimates are significantly different from zero at the 5% level. Total differentiation of (12) indicates that the estimated coefficients measure the percentage change in the share ratios for one-unit changes in the independent variables. All else equal, a one-unit change in the forest rent (fr) decreases the ratio of agricultural to forestland (y_2 / y_1) by 0.005%. Higher forest rents are expected to increase y_1 and decrease y_2, both of which decrease y_2 / y_1. In contrast, an increase in agricultural rents (ar) tends to increase the share ratio by shifting land from forest to agriculture. The coefficient on population density (pd) is not significantly different from zero. If an increase in population density decreases the area of forest and agricultural land in equal proportion, the share ratio remains unchanged. A higher value of lq_1 indicates that a county has lower average quality land, and this tends to decrease the share of agricultural land relative to forest. Conversely, counties with a larger percentage of high quality land (i.e., a larger value of lq_2) tend to have more agricultural land relative to forest.

The results for the second equation of the OLS model are also consistent with expectations. An increase in forest rent (fr) decreases the ratio of urban/other to forestland (y_3/y_1). As discussed above, it is possible for the area of urban/other land to decline, in the present case as a result of conversion to forest. The share ratio increases with population density (pd); however, the coefficient on agricultural rents (ar) is not significantly different from zero, nor is the coefficient on lq_1. Our land quality measure reflects the productivity of land for agricultural uses, and we would not expect the relative share of urban/other land to depend systematically on average land quality. However, counties with a greater share of high quality land (lq_2) tend to have more urban/other land relative to forest. High quality agricultural land tends to be level and accessible and may provide better opportunities for conversion to developed uses. The R-squared statistics indicate that the explanatory variables explain 55% and 44% of the variation in the dependent variables in the two equations.

The results for the dummy variables model are shown in the second column of Table 2. In both equations, we reject the null hypothesis that the dummy variables parameters are zero ($\alpha_{2i} = \alpha_{3i} = 0$ for all i) at the 5% level. This suggests that the explanatory variables in the OLS model do not adequately control for cross-sectional variation in the dependent variables. For instance, the county-level land quality variables may not fully capture land heterogeneity within counties. There may also be omitted relevant factors such as distance to market centers and availability of transportation systems. Given the above result, we would expect the coefficients on the rent variables in the OLS model to measure an amalgam of cross-sectional and

[9] The inclusion of dummy variables tends to ameliorate problems with heteroskedasticity; however, we still test for heteroskedasticity using White's (1980) general test.

[10] We thank Jeff Kline for calling our attention to this point. Also, we refer readers to Chapter 11 of Judge et al. (1988) for further discussion and comparison of the dummy variables and error components models.

Table 2. Estimation results using data from 1964 to 1992.

	Dependent variable = $\ln(y_2/y_1)$ (y_2 = agricultural share, y_1= forest share)		
Variable	OLS	Dummy variables	Error components
Constant	0.96**		0.21
	(0.37)		(0.79)
fr	–0.005**	–0.002**	–0.002**
	(0.0008)	(0.0002)	(0.0002)
ar	0.004**	0.003**	0.003**
	(0.001)	(0.0003)	(0.0003)
pd	–0.05	–0.77*	–0.37
	(0.23)	(0.44)	(0.36)
lq_1	–0.45**		–0.39**
	(0.06)		(0.14)
lq_2	1.98**		2.38**
	(0.39)		(0.85)
Adjusted R^2	0.55	0.98	0.54
$N = 467$			
	Dependent variable = $\ln(y_3/y_1)$ (y_3 = urban/other share, y_1= forest share)		
Variable	OLS	Dummy variables	Error components
Constant	–1.32**		–2.07**
	(0.36)		(0.57)
fr	–0.004**	0.0006	–0.0005
	(0.0007)	(0.0006)	(0.0007)
ar	–0.0005	–0.0009	–0.0009
	(0.001)	(0.0008)	(0.0009)
pd	2.46**	4.18**	2.61**
	(0.22)	(1.27)	(0.34)
lq_1	–0.08		–0.04
	(0.06)		(0.10)
lq_2	2.13**		2.37**
	(0.36)		(0.59)
Adjusted R^2	0.44	0.77	0.43
$N = 467$			

NOTE: Standard errors are in parentheses, * denotes significance at the 10% level, and ** denotes significance at the 5% level.

temporal effects. Interestingly, the rent coefficients in the first equation of the dummy variables model, which we presume better reflect the temporal relationship, are smaller in absolute value than their OLS counterparts. This result is consistent with the notion, discussed above, that land conversions involving forest will be relatively unresponsive to changes in economic conditions. This phenomenon will be reflected in time-series data but will not be revealed in cross-sectional data.

In the dummy variables model, the coefficients on the rent variables are significantly different from zero in the first equation; however, in the second equation, the coefficient on forest rent is insignificant. This result suggests that forest rents do not explain changes in the urban/other to forest ratio, a result also found in Alig and Healy (1987). Moreover, it indicates that the coefficient in the OLS model, which is significantly different from zero, most likely measures the spatial effect of forest rents. The R-squared statistics are substantially larger in the dummy variables model (98% and 77% in the two equations), indicating that the county effects explain a large share of the remaining variation in the dependent variables. In the error components model, the estimated coefficients on the rent variables are similar to those in the dummy variables model. Otherwise, the results for the error components model are similar to those for the OLS model. Using Hausman's (1978) specification test, we reject the null hypothesis that the error components model is the correct specification against the dummy variables alternative.

When we limit the observations to the 1964 to 1982 period, the results for the three models are, for the most part, the same (Table 3). The exception is the rent coefficients in the dummy variables and error components models, which become even smaller. Larger changes are observed when only the 1964 to 1974 observations are used (Table 4). In the first equation of the OLS model, the rent variables have the expected signs but are no longer significantly different from zero. In both equations of the dummy variables model, most of the coefficients are insignificant and have unexpected signs. In this case, the time-series information is so limited that we cannot estimate the temporal effect of the explanatory variables with any precision. The error components model is estimated with a Generalized Least Squares procedure, which fails to provide estimates for the first equation. The results of the second equation are similar to those for the OLS model.

Forecasting Results

In the previous section, we found that the dummy variables model generally outperformed the OLS and error components models. In particular, it appears that

Table 3. Estimation results using data from 1964 to 1982.

	Dependent variable = $\ln(y_2/y_1)$ (y_2 = agricultural share, y_1 = forest share)		
Variable	OLS	Dummy variables	Error components
Constant	0.68		0.14
	(0.43)		(0.80)
fr	–0.004**	–0.0009	–0.001**
	(0.0009)	(0.0002)	(0.0003)
ar	0.004**	0.0009*	0.001**
	(0.002)	(0.0003)	(0.0004)
pd	–0.02	–0.98*	–0.30
	(0.28)	(0.54)	(0.45)
lq_1	–0.43**		–0.39**
	(0.07)		(0.14)
lq_2	2.16**		2.54**
	(0.46)		(0.87)
Adjusted R^2	0.53	0.99	0.52
$N = 333$			
	Dependent variable = $\ln(y_3/y_1)$ (y_3 = urban/other share, y_1 = forest share)		
Variable	OLS	Dummy variables	Error components
Constant	–1.83**		–2.43**
	(0.38)		(0.65)
fr	–0.003**	0.0004	–0.0002
	(0.0008)	(0.00071)	(0.0007)
ar	0.001	0.0007	0.0008
	(0.001)	(0.001)	(0.001)
pd	2.41**	3.42**	2.45**
	(0.27)	(1.87)	(0.41)
lq_1	–0.04		–0.01
	(0.06)		(0.11)
lq_2	2.23**		2.41**
	(0.37)		(0.69)
Adjusted R^2	0.41	0.82	0.41
$N = 333$			

NOTE: Standard errors are in parentheses, * denotes significance at the 10% level, and ** denotes significance at the 5% level.

when a longer time series is used, the dummy variables model provides better estimates of the temporal relationship between the land use share ratios and the rent variables. If this is indeed the case, we would expect the dummy variables model to more accurately predict future forest area. In this section, we evaluate the forecasting accuracy of the models. For each model, the predicted value of the forest share for county i in time t is

$$\hat{y}_{1it} = \frac{1}{1 + e^{\hat{\beta}_2 X_{it}} + e^{\hat{\beta}_3 X_{it}}} \tag{15}$$

where $\hat{\beta}_2$ and $\hat{\beta}_3$ are vectors of the estimated parameters in the first and second equations, respectively, of (12), (13), and (14), and X_{it} is the corresponding vector of the explanatory variables for county i in time t. The forecast error is given by

$$e_{it}^{f} = y_{1it} - \hat{y}_{1it},$$

where y_{1it} is the observed forest share.

We begin with the models estimated with data for 1964 to 1982. Figure 1 depicts the 1987 and 1992 forecast errors for the OLS and dummy variables models. Each point measures the absolute values of the forecast errors for an individual county, where the x-axis coordinate is the error for the OLS model and the y-axis coordinate is the error for the dummy variables or error components model. If the forecast errors for a county are equal, the point lies on the 45° line. If the OLS model error is larger (smaller), the point lies the right (left) of the 45° line. Figure 1 reveals that the dummy variables model produces more accurate forecasts of forest area in 1987 than the OLS model. Moreover, all of the forecast errors for the dummy variables model are below 0.10, whereas many of the forecast errors for the OLS model are in the 0.10 to 0.20 range. The results for 1992 indicate that the dummy variables model produces only slightly more accurate forecasts than the OLS model. Figure 2 illustrates that the forecasting accuracy of the OLS and error components models is similar. In this case, the forecast errors generally lie along the 45° line.

The forecasting accuracy of each model is summarized by Theil's (1961) inequality coefficient, defined as

$$U_t = \frac{\sqrt{\frac{1}{67}\sum_{i=1}^{67}(y_{1it} - \hat{y}_{1it})^2}}{\sqrt{\frac{1}{67}\sum_{i=1}^{67}(y_{1it})^2} + \sqrt{\frac{1}{67}\sum_{i=1}^{67}(\hat{y}_{1it})^2}} \tag{16}$$

Table 4. Estimation results using data from 1964 to 1974.

Variable	Dependent variable = $\ln(y_2/y_1)$ (y_2 = agricultural share, y_1 = forest share) OLS	Dummy variables	Error components
Constant	0.30		
	(0.52)		
fr	–0.002	0.0002	
	(0.001)	(0.0002)	
ar	0.002	–0.0006*	
	(0.002)	(0.0003)	
pd	0.02	0.97	
	(0.38)	(0.83)	
lq_1	–0.40**		
	(0.09)		
lq_2	2.34**		
	(0.57)		
Adjusted R^2	0.50	0.99	
N = 199			

Variable	Dependent variable = $\ln(y_3/y_1)$ (y_3 = urban/other share, y_1 = forest share) OLS	Dummy variables	Error components
Constant	–2.29**		–2.75**
	(0.42)		(0.72)
fr	–0.003**	–0.0007	–0.001*
	(0.001)	(0.0008)	(0.0008)
ar	0.003*	0.003**	0.003**
	(0.002)	(0.001)	(0.001)
pd	2.29**	–0.52	2.29**
	(0.35)	(3.13)	(0.48)
lq_1	0.03		0.05
	(0.07)		(0.13)
lq_2	2.39**		2.52**
	(0.43)		(0.77)
Adjusted R^2	0.39	0.89	0.40
N = 199			

NOTE: Standard errors are in parentheses, * denotes significance at the 10% level, and ** denotes significance at the 5% level. The Generalized Least Squares procedure failed to provide estimates of the first equation of the error components model.

where 67 is the number of counties. U_t is equal to 0 if $y_{1it} = \hat{y}_{1it}$ for all i, and is bounded from above by 1, which indicates the worst possible predictive performance. The inequality coefficient can be decomposed to form bias (U_t^m), variance (U_t^s), and covariance (U_t^c) proportions, defined as

$$U_t^m = \frac{(\bar{\hat{y}}_{1t} - \bar{y}_{1t})^2}{\frac{1}{67}\sum_{i=1}^{67}(y_{1it} - \hat{y}_{1it})^2}$$

$$U_t^s = \frac{(\sigma_{\hat{y}_{1t}} - \sigma_{y_{1t}})^2}{\frac{1}{67}\sum_{i=1}^{67}(y_{1it} - \hat{y}_{1it})^2}, \tag{17}$$

$$U_t^c = \frac{2(1-\rho)\sigma_{\hat{y}_{1t}}\sigma_{y_{1t}}}{\frac{1}{67}\sum_{i=1}^{67}(y_{1it} - \hat{y}_{1it})^2}$$

where $\bar{\hat{y}}_{1t}$, $\bar{y}_{1t}$, $\sigma_{\hat{y}_{1t}}$, and $\sigma_{y_{1t}}$ are the means and standard deviations of the predicted and actual values, respectively, ρ is their correlation coefficient, and $U_t^m + U_t^s + U_t^c = 1$. As discussed by Pindyck and Rubinfeld (1981), U_t^m indicates the bias in the forecast (the degree to which the means of the predicted and actual values differ), U_t^s indicates how well the predicted values replicate variability in the actual values, and U_t^c measures the remaining unsystematic error in the forecast.

The inequality coefficients reported in the second column of Table 5 confirm the results in Figures 1 and 2 that the dummy variables model outperforms the OLS model and the OLS and error components models have similar forecasting accuracy. The decomposition of the inequality coefficients reveals that, with all the models, most of the error is measured by the covariance proportion U_t^c. This finding provides support for the econometric models because it indicates that the forecast error is largely unsystematic. A finding to the contrary would cast doubt on the model specifications. Among the three models, the dummy variables model has the largest value of U_t^c, followed by the error components and OLS models.

The inequality coefficients characterize the ability of the model to predict forest area in individual counties; however, for some policy applications, the state-level forecast may be of primary interest. In Table 5, we report the actual state forest area and the forecasted values for each model. The OLS model

Table 5. The accuracy of forest area forecasts from models estimated with data from 1964 to 1982.

Forecast year	Model	State-level forest area (1,000 ha)	Theil's inequality coefficient (U) and decomposition into proportions of inequality (U^m, U^s, U^c)*				
			U	U^m	U^s	U^c	$U^m+U^s+U^c$
1987	Actual	8,381					
	OLS	8,611	0.072	0.083	0.093	0.837	1.00
	Dummy variables	8,364	0.026	0.013	0.016	0.986	1.00
	Error components	8,350	0.077	0.008	0.112	0.895	1.00
1992	Actual	8,433					
	OLS	8,594	0.075	0.039	0.123	0.852	1.00
	Dummy variables	8,337	0.051	0.036	0.023	0.956	1.00
	Error components	8,325	0.083	0.000	0.129	0.886	1.00

* Theil's inequality coefficient (U) and the proportions of inequality (U^m, U^s, and U^c) are defined in Equations (16) and (17), respectively.

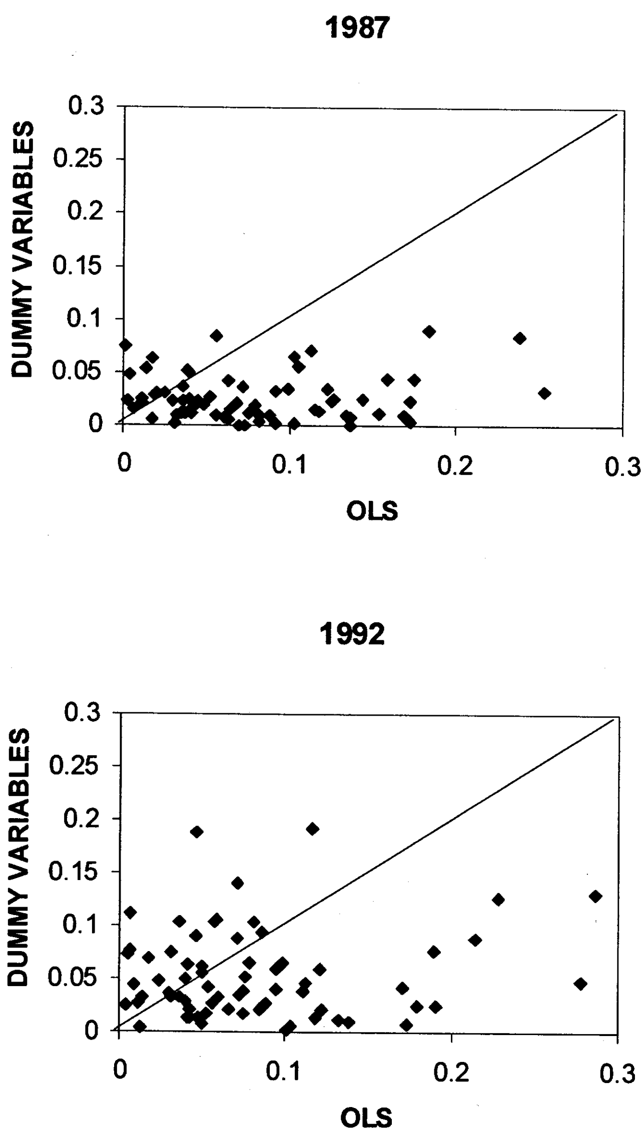

Figure 1. A comparison of 1987 and 1992 forecast errors for OLS and dummy variables models estimated with data for 1964 to 1982.

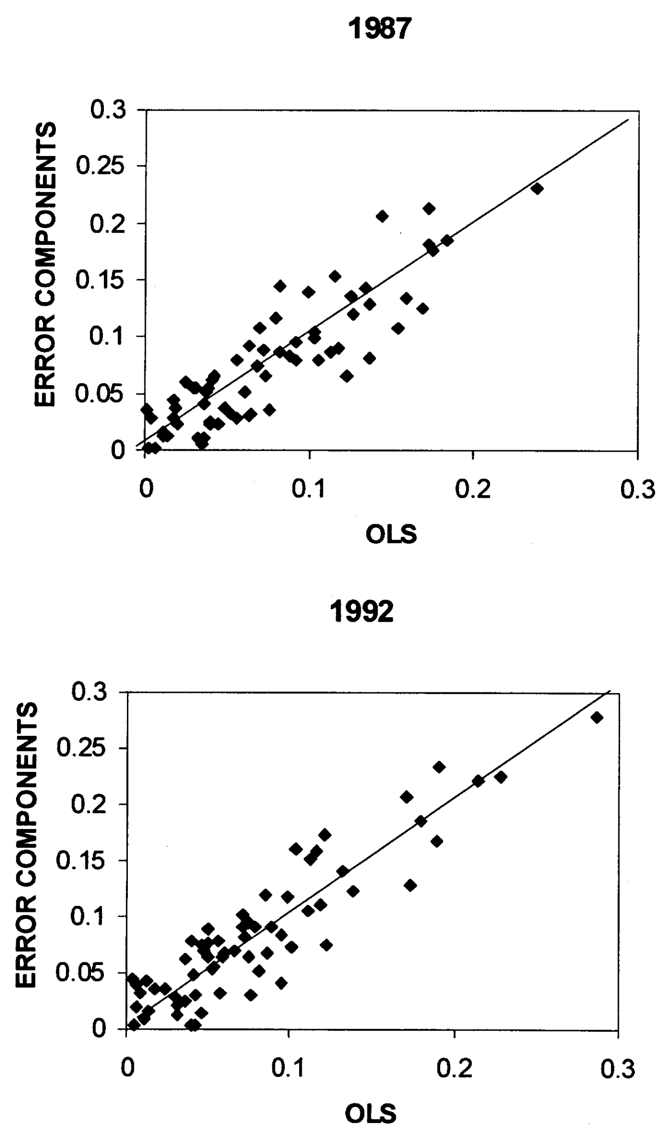

Figure 2. A comparison of 1987 and 1992 forecast errors for OLS and error components models estimated with data for 1964 to 1982.

forecasts are about 230 and 160 thousand ha too high in 1987 and 1992, respectively. The dummy variables and error components models produce more accurate as well as similar results. The aggregate forecast errors for the dummy variables model are about –17 thousand and –96 thousand ha in 1987 and 1992, respectively. The corresponding values for the error components model are approximately –31 thousand and –108 thousand ha. This result may seem at odds with the finding of similar inequality coefficients for the OLS and error components models. Note, however, that negative and positive forecast errors cancel each other when the state-level forecast is computed, whereas in Equation (16), the errors are squared and, thus, do not cancel each other when summed.

Turning to the models estimated with data for 1964 to 1974, we find that the dummy variables model produces more accurate forecasts than the OLS model for 1978, 1982, and 1987. Graphs of forecast errors (not shown) are similar to the graph in the top panel of Figure 1. As the length of the forecast increases, however, the relative accuracy of the dummy variables model predictions diminishes. For the 1992 forecast, the dummy variables model produces only slightly better forecasts. These results are confirmed by the inequality coefficients in the second column of Table 6. Interestingly, the values for the OLS model are roughly constant, indicating that the accuracy of the forecasts does not decline with the length of the forecast. In contrast, the values for the dummy variables model increase steadily. As with the models estimated with the 1964 to 1982 data, most of the error in the forecasts is unsystematic, particularly in the case of the dummy variables model. Finally, comparison of the state-level predictions reveals that the aggregate forecast errors for the OLS and dummy variables models are similar in 1978 and 1992, though opposite in sign, and the aggregate errors for 1982 and 1987 are considerably smaller for the dummy variables model.

Conclusions

Forest policy analysts have increasingly used econometric methods to forecast forestland area. The econometric land use studies conducted during the 1980s produced mixed results; however, in the last decade, land use models have improved in part because researchers recognized the importance of controlling for spatial differences in land quality. Nevertheless, it is unclear that this new generation of land use models can provide more accurate forecasts of forest area. The decision to allocate land to forest is a fundamentally dynamic process and, thus, time-series data is needed to measure the temporal relationship between forest area and explanatory variables. Unfortunately, available data sets provide few time-series observations, and researchers have had to estimate land use models with pooled time-series and cross-sectional data. The challenge is to adequately control for cross-sectional variation—by including land quality variables, for instance—so that the limited temporal information can be used to measure underlying dynamic relationships. Of central importance for projections is the relationship between land area and economic decision variables such as land rents.

The central issue addressed in this article is whether or not land use models adequately measure the dynamic decision process governing forestland allocation and, thus, provide a means of accurately predicting future forest area. We begin by estimating a standard version of the model with the full set of pooled data (the OLS model). The results are plausible in that the estimated coefficients have expected signs and, in appropriate cases, are significantly different from zero. However, when we consider the dummy variables model, we reject the implicit restrictions imposed by the OLS model. This suggests that the OLS model does not adequately control for cross-sectional variation in the dependent variables and that, as a consequence, the parameters on the rent variables measure a combination of spatial and temporal effects. Indeed, the forest rent coefficient in the first equation of the OLS model is over twice its value in the dummy variables model, which we presume to be a better measure of the temporal relationship. Also, the forest rent coefficient in the second equation of the OLS model appears to primarily measure spatial variation.

In light of our estimation results, we would expect the dummy variables model to provide more accurate forecasts

Table 6. The accuracy of forest area forecasts from models estimated with data from 1964 to 1974.

Forecast year	Model	State-level forest area (1,000 ha)	Theil's inequality coefficient (U) and decomposition into proportions of inequality (U^m, U^s, U^c)*				
			U	U^m	U^s	U^c	$U^m+U^s+U^c$
1978	Actual	8,289					
	OLS	8,320	0.078	0.026	0.124	0.865	1.00
	Dummy variables	8,243	0.018	0.017	0.058	0.940	1.00
1982	Actual	8,328					
	OLS	8,586	0.079	0.026	0.124	0.865	1.00
	Dummy variables	8,314	0.026	0.001	0.049	0.966	1.00
1987	Actual	8,381					
	OLS	8,595	0.075	0.026	0.124	0.865	1.00
	Dummy variables	8,322	0.033	0.027	0.011	0.977	1.00
1992	Actual	8,433					
	OLS	8,573	0.078	0.026	0.124	0.865	1.00
	Dummy variables	8,297	0.054	0.049	0.019	0.947	1.00

* Theil's inequality coefficient (U) and the proportions of inequality (U^m, U^s, and U^c) are defined in Equations (16) and (17), respectively.

of forest area. This outcome is confirmed by the forecast error plots in Figure 1 and the computed values of the inequality coefficients in Tables 5 and 6. Figure 1 reveals that the dummy variables model rarely produces county-level forecasts of the forest share that are off by more than 0.10. In contrast, Figures 1 and 2 show that many of the OLS and error components model forecast errors are between 0.10 and 0.20. In addition to providing more accurate predictions for individual counties, the dummy variables model outperforms the OLS model in forecasting state-level forest area. Also, the decomposition of the inequality coefficients reveals that, of the three models, the dummy variables model has the highest proportion of unsystematic forecast error, although the proportion is relatively high for all models.

The estimation and forecasting results for the OLS and error components models are similar (Figure 2 and Tables 5), with two exceptions. The error components model produces more accurate state-level forecasts. While there is little difference between the two models in their ability to predict forest area for individual counties, it appears that, on average, the error components model produces more accurate forecasts. In addition, the decomposition of the inequality coefficients reveals that the error components model has a higher proportion of unsystematic forecast error than the OLS model.

When the observations are limited to the years 1964 to 1974, there is not enough temporal information to precisely estimate the coefficients of the dummy variables model. Nonetheless, the dummy variables model produces more accurate forecasts of forest area than the OLS model at the county and state level. However, as the length of the forecast increases, the advantage of using the dummy variables model decreases. Interestingly, the accuracy of the OLS model predictions is invariant to the forecast length. One possible explanation for these results is that the dummy variables model measures short-term responses to rent changes, whereas the OLS model captures the long-term response. This reasoning is consistent with the smaller rent coefficients estimated for the dummy variables model. In the OLS model, the rent coefficients measure, to some degree, the effects of spatial differences in the variables. Thus, we might interpret the coefficients as the response to a sustained change in rents reflecting the full adjustment of land use allocations on the part of landowners.[11]

The foregoing discussion argues for the use of the dummy variables model, particularly if it is to be used for near-term forecasting. In the RPA analyses, for instance, econometric models are used to project land areas at different points in time over a 50 yr period, assuming a sequence of prices and other exogenous variables. The dummy variables model is favored for this application; however, one could make a case for using the OLS model if the objective is to measure the long-term response to permanent changes in the independent variables. In general, we find that the dummy variables model is preferable to the error components model, suggesting that the source of unmeasured differences across counties is structural rather than random. Lastly, we have discussed the forecasting accuracy of the different models relative to each other, but not relative to the actual forest area. While this is a matter of judgment, it is clear that the models produce state-level estimates that are close by most standards to the actual values. Furthermore, in more cases than not, the models correctly predict the direction of the observed change in forest area.

In conclusion, we find that econometric land use models are an effective tool for forecasting forest area. These models are particularly useful for policy analysis since they explicitly measure landowner responses to decision variables that can be affected by land use policies. For example, Plantinga et al. (1999) and Stavins (1999) examine the effects of afforestation subsidies on land use decisions by simulating increases in rents from forestry. We should, however, note some limitations of this approach. Perhaps the most important caveat is our assumption that there are no changes in the underlying structural relationships, either during the historical period analyzed or the forecast period. The model structure, however, is shaped by the policy environment and this certainly changes over time. For instance, between 1964 and 1992, U.S. farm program provisions were modified frequently, and the Conservation Reserve Program introduced in 1986 encouraged the establishment of permanent vegetative cover including trees. Statistical tests can be used to test for changes in model parameters over time, and this is a topic left for future research. A greater challenge is posed by the possibility of structural changes in the future. For instance, the 1996 farm bill (the Federal Agricultural Improvement and Reform Act) phases out many of the traditional price and income support programs. This movement toward free markets for agricultural commodities may compromise the forecasting ability of econometric models estimated with data from periods during which traditional farm programs were in effect.

[11] As an analogy, researchers often use cross-sectional data on firms to estimate long-run production relationships because capital stocks vary across firms.

Literature Cited

ALIG, R.J. 1986. Econometric analysis of forest acreage trends in the Southeast. For. Sci. 32(1):119–134.

ALIG, R.J., AND R. HEALY. 1987. Urban and built-up area changes in the United States: An empirical investigation of determinants. Land Econ. 63(3):215–226.

BALESTRA, P., AND M. NERLOVE. 1966. Pooling cross section and time series data in the estimation of a dynamic model: The demand for natural gas. Econometrica 34(3):585–612.

BIRDSEY, R.A. 1992. Carbon storage and accumulation in United States forest ecosystems. USDA For. Serv. Gen. Tech. Rep. WO-59.

DIXIT, A.K., AND R.S. PINDYCK. 1994. Investment under uncertainty. Princeton University Press, Princeton, NJ.

DUBOIS, M.R., K. MCNABB, AND T.J. STRAKA. 1997. Costs and cost trends for forestry practices in the South. For. Landowner 56(2):7–13.

HALLBERG, M.C. 1992. Policy for American agriculture: Choices and consequences. Iowa State University Press, Ames, Iowa.

HARDIE, I., AND P. PARKS. 1997. Land use with heterogeneous quality: An application of an area base model. Am. J. Agric. Econ. 77:299–310.

HAUSMAN, J.A. 1978. Specification tests in econometrics. Econometrica 46:1251–1272.

HOWARD, J.L. 1997. U.S. timber production, trade, consumption and price statistics 1965–1994. USDA For. Serv. Gen. Tech. Rep. FPL-GTR-98.

JUDGE, G.G., R.C. HILL, W.E. GRIFFITHS, H. LUTKEPOHL, AND T.C. LEE. 1988. Introduction to the theory and practice of econometrics. Wiley, New York.

LICHTENBERG, E. 1989. Land quality, irrigation development, and cropping patterns in the Northern High Plains. Am. J. Agric. Econ. 71:187–94.

MADDALA, G.S. 1983. Limited dependent and qualitative variables in econometrics. Econ. Soc. Monogr. No. 3. Cambridge University Press, New York.

MAULDIN, T., A.J. PLANTINGA, AND R.J. ALIG. 1999. Land use in the Lake States Region: Analysis of past trends and projections of future changes. USDA For. Serv. Res. Pap. PNW-RP-519.

MILLER, D.J., AND A.J. PLANTINGA. 1999. Modeling land use decisions with aggregate data. Am. J. Agric. Econ. 81(1):180–194.

NERLOVE, M. 1971. Further evidence on the estimation of dynamic economic relations from a time series of cross sections. Econometrica 39(2):359–381.

PARKS, P.J., AND R.A. KRAMER. 1995. A policy simulation of the Wetlands Reserve Program. J. Environ. Econ. Manage. 28(2):223–240.

PARKS, P.J., AND B.C. MURRAY. 1994. Land attributes and land allocation: Nonindustrial forest use in the Pacific Northwest. For. Sci. 40(3):558–575.

PINDYCK, R.S., AND D.L. RUBINFELD. 1981. Econometric models and economic forecasts. McGraw-Hill, New York.

PLANTINGA, A.J. 1996. The effect of agricultural policies on land use and environmental quality. Am. J. Agric. Econ. 78(4):1082–1091.

PLANTINGA, A.J., T. MAULDIN, AND R.J. ALIG. 1999. Land use in Maine: Determinants of past trends and projections of future changes. USDA For. Serv. Res. Pap. PNW-RP-511.

PLANTINGA, A.J., T. MAULDIN, AND D.J. MILLER. 1999. An econometric analysis of the cost of sequestering carbon in forests. Am. J. Agric. Econ. 81(4):812–824.

SCHATZKI, S.T. 1998. A theoretical and empirical examination of land use change under uncertainty. Ph.D. Diss,, Harvard University, Cambridge, MA.

STAVINS, R. 1999. The costs of carbon sequestration: A revealed-preference approach. Am. Econ. Rev. 89(4):994–1009.

STAVINS, R., AND A. JAFFE. 1990. Unintended impacts of public investment on private decisions: The depletion of forest wetlands. Am. Econ. Rev. 80(3):337–352.

THEIL, H. 1961. Economic forecasts and policy. North-Holland, Amsterdam, The Netherlands.

U.S. DEPARTMENT OF AGRICULTURE. 1973. Land capability classification. Soil Conserv. Serv. Agric. Handb. No. 210.

USDA FOREST SERVICE. 1988. The South's fourth forest: Alternatives for the future. For. Resour. Rep. No. 24.

USDA FOREST SERVICE. 1990. An analysis of the timber situation in the United States: 1989–2040. Gen. Tech. Rep. RM-199.

WHITE, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48:817–838.

WU, J., AND K. SEGERSON. 1995. The impact of policies and land characteristics on potential groundwater pollution in Wisconsin. Am. J. Agric. Econ. 77:1033–1047.