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PUBLIC AND PRIVATE FOREST DISTURBANCE REGIMES IN THE SOUTHERN APPALACHIANS

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ABSTRACT. The choice to harvest timber depends on, among other things, the accessibility and location of the forest. This paper examines observed harvest choices derived from satellite imagery and tests for relationships between harvest probability and location, quality, and ownership attributes of the site. Results indicate that the overall probability of harvesting for public lands is significantly lower than for private lands. Substantially different disturbance patterns relative to location attributes are also established for these groups. Results suggest a way to include spatially explicit information regarding private land management in public land management plans. An example demonstrates how alternative uses of public lands might be considered in the broader context of a multiple ownership landscape.

KEY WORDS: Harvest choice model, ecosystem management, national forests.

1. Introduction. Public forests are increasingly seen as instruments for enhancing biodiversity and ecological health. Most notably, the U.S. Forest Service has sought to define and apply principles of "ecosystem management" on national forests (e.g., Salwasser [1990]). This approach to management emphasizes ecosystem condition and ecological health, which depend crucially on the spatial configuration of conditions within a forested landscape. Such spatial configurations are heavily influenced by both human activities and the biological processes of regeneration, growth and mortality, and relevant ecosystem boundaries may extend beyond public land. Activities by private landowners therefore influence the ability of public land managers to provide for biodiversity and ecological health. The spatial dynamics of forest cover on both public and private land need to be considered when assessing the potential ecological impacts of public land management.

This paper examines timber harvesting, the most pervasive cause of forest cover change on both public and private land. It analyzes the influences of spatial or locational variables on harvest intensity and the resulting location of harvested areas, and it compares harvest intensities on public and private land. Our approach was to test for the influences of various factors on harvest decisions and to compare the decisions of public and private landowners using empirical models of harvesting behavior. The general form of the models was developed from economic (utility) theory, and coefficients were estimated from changes in forest cover interpreted from satellite imagery and other spatially referenced data. In addition to providing for hypothesis tests, the model estimates can be used to predict future disturbance probabilities. Results can be mapped to define areas where the probability of disturbance is especially high. Accordingly, and because we use data readily available in most applications of Geographic Information Systems (GIS) to forestry, these models may prove useful for "ecosystem management."

2. **Methods.** Public and private ownership define two very different institutional settings for managing forest lands. While private owners are largely motivated by market signals, public ownership of forests is generally motivated by market failure related to the production externalities of timber harvesting on private lands. This suggests (1) that public land managers are guided by a broader complement of goals related to multiple-use and (2) that the outcomes of their management should therefore be distinct from outcomes observed on private land. This study tests for differences in outcomes.

To examine the effects of these different institutional settings on forest management, we compare the likelihood of harvesting timber on the two ownerships. The simplest way to make this comparison is to measure differences in the proportion of forest land harvested by the groups in a given period. However, differences in harvest intensity may merely reflect substantial differences in the quality and the location of forested lands by ownership group. Even without the aforementioned differences in motivation, quality and location influence both the costs and revenues of forest management and other land uses, thereby implying differences in optimal management approaches.

To account for differences in land quality, we model the probability of harvest as a function of variables which describe the particular site. This model is generally derived from decision making processes that differ between ownerships but depend on similar variables. For private land, theory suggests that utility comparisons frame the binary choice between harvesting and not harvesting. Variables that influence utility are therefore reflected in the observed harvest choice. Three types of variables are likely to influence the harvest choice: (1) price variables-the price of delivered logs as well as prices for other services potentially derived from the land, (2) ownership variables----for example, previous studies have shown that income of the landowner may influence harvest decisions (Binkley [1 WI]), and (3) site variables—defining the location of the site relative to the transportation network and to where its products arc marketed, as well as factors that influence the costs of harvesting (e.g.. steepness of the site).

For public lands we posit that decisions arc also guided by utility comparisons, though expanded beyond the private model to consider, for example, the visual and wildlife habitat impacts of harvest activities. In this context, harvest choices still depend on a complement of forest values and on site variables that hold similar influence over costs for both public and private owners.

For the analysis conducted here, the spatial breadth is limited to a small area with a single marketing site and the temporal breadth is limited to a single period of time. This means that, prices (delivered prices, that is) are invariant, for the data set. In effect, by sampling in cross-section, we control for variation in delivered pi-ices. Furthermore, we cannot map ownership characteristics to specific sites, so that variation in utility is derived strictly from variation in site variables.

Accordingly, utility is defined as

$$U_{j,i} = f_i(X_j) \tag{1}$$

where utility of choice i (either to harvest, $i = 1$, or to delay, $i = 0$) at site j (U_{ji}) depends on a vector of site characteristics (X_j). Utility comparisons result in management decisions and define the binary variable, Y_j as

$$Y_j = \begin{cases} 1, & \text{if } U_{j1} > U_{j0} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

$Y_j = 1$ indicates a decision to harvest and implies that the utility of harvesting exceeds the utility of delaying harvest. $Y_j = 0$ indicates no harvest.

Given this binary choice framework, we sought to explain the probability of harvest ($\text{PR}\,[Y_j = 1]$) based on the implicit difference in utility derived from the two alternatives ($U_{j1} - U_{j0}$):

$$\begin{aligned} \text{PR}\,(Y_j = 1) &= \text{PR}\,(U_{j1} > U_{j0}) \\ &= \text{PR}\,(f_1(X_j) > f_0(X_j)) \\ &= F(X_j'\beta) \end{aligned} \tag{3}$$

where F is a cumulative distribution function (cdf) of the difference in utilities (see Binkley [1981]). We selected the binary logit model (i.e., we selected a logistic cdf for F) to model the harvest/no harvest decision.[1] The logit model is defined as:

$$F(X_j'\beta) = \frac{1}{1 + e^{X_j'\beta}} \tag{4}$$

so that the probability of harvest on a particular site is a function of its various attributes.

Earlier applications of empirical harvest choice models include Binkley [1981] and Dennis [1990]. Others (Dennis [1989], Kuuluvainen and Salo [1991]) have applied discrete choice models to the simultaneous decisions of whether to harvest and how much to harvest. These previous studies have, however, focused on the effects of temporally variable stumpage prices and ownership characteristics on decisions. In contrast, the small-site application developed here allows us to focus on spatial factors that determine a site's comparative (locational) advantage.

Logit models of harvest choice are estimated for the two ownerships. Coefficient estimates and likelihood functions then provide information needed to compare the probability of harvesting on these lands and to examine the relationships between site features and harvest probability within a particular ownership. In addition, coefficient estimates can also be used to predict the probability of harvest for a particular site defined by the independent variables X_j using equation (4) directly. These predicted harvest probabilities may provide useful information for public forest planning. The hypothesis tests are discussed in the next section and the application of predicted harvest probabilities is described in the discussion of results.

3. Hypotheses.

3.1. *Ownership effects.* We posited that, because public and private land managers are motivated by different kinds of incentives (and because public managers must account for additional spatially explicit consequences of their harvest decisions), the influence of site attributes on harvest decisions would differ between ownership groups. We tested the null hypothesis of no difference between groups using a likelihood ratio test with pooled and separate models. The separate effects model was constructed by introducing a dummy variable for ownership ($D_j = 1$ for U.S. Forest Service land and $D_j = 0$ otherwise) that shifted both the intercept and the coefficients of independent variables (e.g., see Pindyk and Rubenfield [1981]):

$$F(\cdot) = X_j'\beta + D_j X_j'\gamma \tag{5}$$

The pooled model was constructed by constraining all interaction terms (γ) defined by the dummy variable to zero. The resulting chi-squared statistic has degrees of freedom equal to the number of these constraints (i.e., the number of explanatory variables including the intercept).

3.2. *Temporal effects.* Forest cover change was observed for two different time periods (1975–1980 and 1980–1986). If the value of forest products or any other factor that was spatially invariant differed substantially between periods, then the probability of harvest should be affected. While our time periods do not coincide perfectly with any measure of a business cycle, hardwood lumber prices were generally higher for the period 1975–1980 than for 1980–1986. We tested the hypothesis of no difference between periods by applying the method used to test for ownership effects (i.e., using a dummy variable with interaction terms) with the dummy variable equal to one for observations in the period 1980–1986 and zero otherwise.

3.3. *Decision variables.* We tested for the explanatory power of each independent variable in X as well as the power of each model as a whole. The significance of the influence of each independent variable on harvest choice was tested using t-statistics. The likelihood values for fitted models and null models (where all coefficients except the intercept were set to zero) defined a likelihood ratio test for the hypothesis of no explanatory power for the model as a whole (Judge et al. [1985, p. 767]). The likelihood ratio has a chi-squared distribution with degrees of freedom equal to the number of explanatory variables (exclusive of the intercept).

4. Data. Our study site is Macon County, in the Little Tennessee River Basin in western North Carolina. Macon County is in the southern Appalachian mountains and exhibits a variety of conditions and land uses. It is a rural area with a centrally located county seat, Franklin, which is generally the hub of intracounty transportation. Lands are held in both private and public ownership with the U.S. Forest Service being the principal public ownership.

All data used for this project were compiled as maps in the Geographic Information System (GIS) GRASS (USACERL) constructed for the study area. A GIS is a computerized mapping system for the entry, storage and display of spatial data for a geographic area. The area is divided into regular grid cells (in this case, cells are 90 meters on a side), defining a raster-based GIS (the alternative is a vector-based GIS that directly stores map boundaries and features). For each data type, data are entered as a map with condition values assigned to each grid cell. These conditions may be continuous variables (e.g., slope) or classes (e.g., National Forest versus private ownership).

Maps of land cover were defined from interpretations of Landsat MSS images for three years: 1975, 1980 and 1986. Values of the dependent variable (Y_j) were defined by comparing land cover in sample cells for those years. If a forested cell changed to a disturbed or grassy cover type in the subsequent period, Y_j was set at 1 to indicate harvest.

Otherwise, Y_j was set at zero. Cells with other initial cover types were not considered in this study. The sample was constructed using a regular grid, and the resulting sample sizes were 1128 for the period 1975–1980 and 1092 for 1980–1986.

Note that the dependent variable is not explicitly defined as a timber harvest. Rather we used disturbed forest cover to proxy for a harvest. This approach may not have captured low-intensity selection harvests, but it should capture most forest harvesting activities. In addition, we cannot make a direct inference regarding the subsequent use of the disturbed land. These types of changes go beyond the scope of this study.

The probability of a forest disturbance is modeled here as a function of four spatially referenced independent variables that, along with a constant, comprise the X_j vector in equation (4): (1) the distance between the site and the nearest paved road, (2) the distance from the road location defined by 1) to the market center (Franklin, North Carolina)[2], (3) the slope of the site, and (4) the elevation of the site. The first two variables define the location of an area relative to the market site and proxy for the costs of access and transportation. The slope of the site proxies for the cost of harvesting timber. We posit that elevation may proxy for species composition as well as access cost. We defined ownership for every site as either private or national forest. We eliminated all observations in wilderness areas and in the Coweeta Experimental Watershed. The former are not managed for timber production while management in the latter is defined by a research program.

The resulting logit models (equation 4) were fitted for both ownerships using maximum likelihood techniques implemented in the software package GAUSS. The Newton-Raphson gradient-based algorithm was used to maximize likelihood functions.

5. Results. The proportion of sampled cells that changed from forest to nonforest cover within a period defines the average probability of a forest disturbance. For private forests in Macon County, the average disturbance probabilities were 0.0691 and 0.0559 for the periods 1975–1980 and 1980–1986, respectively; corresponding values for public lands were 0.005 and 0.012. The average probability of disturbance was much higher on private lands than on public lands.

To test for differences in the disturbance probabilities on private and public lands, we treated the sampled cells as independent Bernoulli trials and calculated confidence intervals for the difference of disturbance probabilities between ownerships (see Larson and Marx [1981, p. 343]).[3] For the period 1975–1980, the 95% confidence interval for the difference in probabilities is (0.0691 − 0.0038) +/− 0.0559; for 1980–1986 it is (0.0592 − 0.0122) +/− 0.0223. In both periods, the confidence intervals do not include zero, indicating that the disturbance probabilities are significantly different for the two ownerships.

However, differences in disturbance probabilities may simply reflect the differences in the quality and locations of public and private land. For example, land held by the U.S. Forest Service is generally more remote than private land. To account for these differences in the land managed by the two ownerships, we used the logit models defined by equations (1)–(4) to test for differences in disturbance regimes.

Estimates of the logit models and hypothesis tests are displayed in Tables 1-3. Tests for identical disturbance regimes on private and public lands—i.e., that the relationship between site attributes and harvest probabilities are identical—were constructed for both periods. The results of these tests are displayed in rows 1 and 2 of Table 1. The hypothesis of identical disturbance regimes on the two ownerships was rejected (at the 1 percent level) for the period 1975–1980. However, for the period 1980–1986, we could not discern between the disturbance regimes on the two ownerships. That is, after accounting for differences in land attributes, we found a significant difference in disturbance regimes in the first period but not in the second.

The logit models do not, however, include all factors that might help explain harvesting decisions. While the model addresses locational attributes, it does not consider characteristics that vary over time rather than space. These include timber prices, population dynamics, etc. To examine the aggregate effects of variables that changed between periods, we tested for the stability of the disturbance regimes between the two sampled periods. Rows 3 and 4 in Table 1 show the outcome of stability tests for private and public lands, respectively. In both cases, the outcome is a failure to reject the hypothesis that disturbance regimes are identical between periods. In spite of differences in timber

TABLE 1. Log-likelihood ratios and chi-squared values for various structural hypotheses regarding harvesting decisions.

Hypothesis	Degrees of Freedom	Log-Likelihood Ratio	Critical χ^2 Value ($p = 0.01$)	Result
1) $H_0 : \beta_{80}^R = \beta_{80}^U$ *	5	24.1383	15.086	Reject
2) $H_0 : \beta_{86}^R = \beta_{86}^U$	5	4.4683	15.086	Accept
3) $H_0 : \beta_{80}^R = \beta_{86}^R$	5	4.3375	15.086	Accept
4) $H_0 : \beta_{80}^U = \beta_{86}^U$	5	13.4329	15.086	Accept
5) $H_0 : \beta^R = 0$	4	149.5141	13.277	Reject
6) $H_0 : \beta^U = 0$	4	1.1531	13.277	Accept

* The subscript refers to coefficients for ownership groups (R = private, U = public). Subscripts define the sample period (80 = 1975–1980, 86 = 1980–1986). No subscript indicates the use of the separate effects model defined by equation (7) using dummy variables.

prices, the disturbance regimes for the two ownerships did not change significantly between periods. Accordingly, we may construct a pooled model—i.e., data pooled for the two periods—to examine the effects of site attributes on harvest probability.

Logit estimates for data pooled between the two periods (Tables 2 and 3) provide more detailed insights into the disturbance regimes of the two ownerships. On private land, the logit coefficients (Table 2) indicate negative relationships between all independent variables (slope, distance to roads, distance to Franklin, and elevation) and the probability of disturbance. All coefficients except elevation are significant at the 5 percent level, and signs are consistent with our expectations regarding the influence of location, slope and elevation on harvesting—i.e., higher costs reduce the probability of harvest.

The estimates of the logit coefficients (β) were also used to estimate the marginal influence of each independent variable on the probability of harvest.[4] The marginal effects coefficients in Table 2 indicate that the probability of harvest, calculated at the means of the independent variables, is most sensitive to the distance between the site and the nearest road and the slope of the site.

TABLE 2. Logit estimates and marginal effects for forest disturbance on private lands. Estimates are derived from the pooled model with observations for both periods (1975–1980 and 1980–1986).

Variable (units)	Logit Coefficient	Standard Error	Marginal Effect*
Constant	1.4557	0.566†	—
Elevation (meters above sea level)	-0.0013	0.001	-0.13
Distance to road (no. of pixels)	-0.0779	0.034‡	-7.50
Distance to Franklin (no. of pixels)	-0.0039	0.001†	-0.39
Slope (degrees)	-0.1355	0.023†	-12.67

* Marginal effects are measured as the percentage change in the probability of harvest for a one percent change in the value of the independent variable. These values are conditional on the value of the independent variables (see equation (6)) and marginal effects are calculated here for the mean values of the sample.

† Indicates significance at the one percent level.

‡ Indicates significance at the five percent level.

We also tested for the overall significance of the logit models. This required comparing the values of the likelihood function for the estimated model with one calculated for the model with coefficients constrained to zero. The results of this test on private land (row 5, Table 1) indicate rejection of the hypothesis of no explanatory power—i.e., the model, as a whole, provides significant explanation of forest disturbance.

On public land, however, the results are much different. Logit coefficients and standard errors (Table 3) show that none of the site attributes are significant in explaining forest disturbance. Accordingly, we can discern no significant relationship between site quality and location and the probability of harvest on public land. In addition, we fail to reject no explanatory power for the model, indicating that information regarding quality and location does not improve the ability to predict the disturbance probability. Factors other than location

TABLE 3. Logit estimates and marginal effects for forest disturbance on public lands. Estimates are derived from the pooled model with observations for both periods (1975–1980 and 1980–1986).

Variable (units)	Logit Coefficient	Standard Error	Marginal Effect*
Constant	-2.555	2.131	—
Elevation (meters above sea level)	-0.001	0.002	-0.18
Distance to road (no. of pixels)	0.003	0.058	0.33
Distance to Franklin (no. of pixels)	-0.001	0.004	-0.05
Slope (degrees)	-0.0116	0.057	-1.15

* Marginal effects are measured as the percentage change in the probability of harvest for a one percent change in the value of the independent variable. These values are conditional on the value of the independent variables (see equation (6)) and marginal effects are calculated here for the mean values of the sample.

† Indicates significance at the one percent level.

‡ Indicates significance at the five percent level.

and site quality (as defined by the variables measured here) explain the decisions of Forest Service managers.

The lack of any significant relationships between locational variables and disturbance seems consistent with spreading harvest activities out over a landscape to avoid large clearings and to address other multiple use goals. Forest management goals defined in planning documents for Nantahala and Pisgah National Forests (U.S.D.A. Forest Service [1992]) include "providing for a more visually pleasing and diverse forest" and rehabilitation of damaged ecosystems. The resulting forest management activities would not necessarily be arranged according to a cost-minimizing strategy but would, by definition, disperse activities across the landscape.

Taken as a whole, these results indicate that while the harvest choice

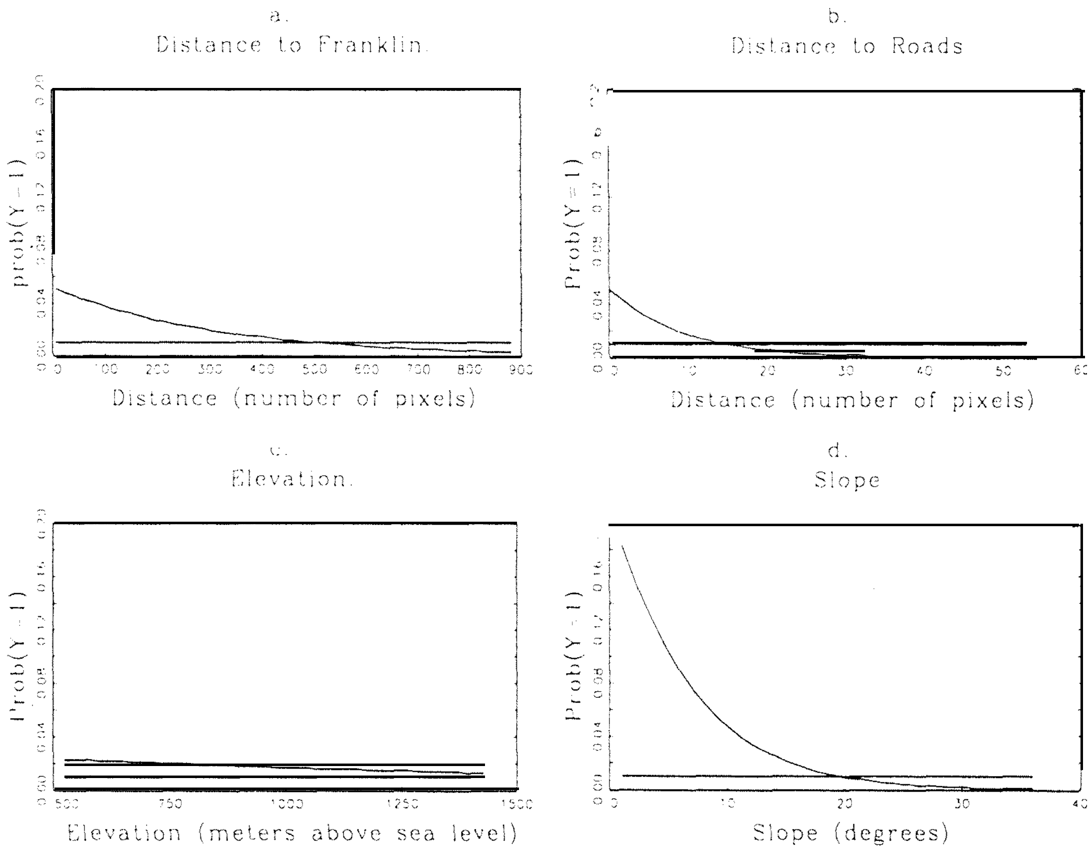

FIGURE 1. Probability of forest disturbance as a function of the referenced variable (all other variables are set at their mean values). In each panel. the downward sloping line is the probability relationship for private land and the horizontal line refers to public land.

model has significant explanatory power on private land, it does not explain the decisions of public land managers. Accordingly, for public land, disturbance probabilities derived front the logit model are no more precise than the average disturbance probability for the ownership as a whole. In contrast, the best estimates for disturbance probabilities on private land are defined by the logit model, which accounts for the influence of site quality and location.

The implications of these results can be examined further by plotting the effects of the locational and site quality variables on disturbance probabilities. The panels of Figure 1 chart, the influence of each of the four independent variables on the probability of disturbance (Prob $[Y_j = 1]$) using equation (4). For each panel, the value of the referenced independent variable is varied across its observed range, while the other variables are held at their mean values. For private lands, probability lines slope downward from left to right. For public land, the lines are horizontal at the average disturbance probability. The figure highlights the especially important influence of slope on private disturbance probabilities. The calculated probability is approximately 0.18 at 1 degree slope and approaches 0.00 at about 32 degrees slope.

On private land, the probability of disturbance declines as the value of each independent variable increases. At low values of each independent variable. the probability of disturbance on private lands is substantially higher than that on public lands. However, its the value of the independent variable increases, the private probability declines and eventually intersects tho probability of disturbance for public land (the exception is elevation, where the disturbance probability is everywhere lower on the public land). At this point and beyond, the probability of disturbance is higher on public lands. Thus, while average disturbance probabilities are much higher on private land, over a small portion of the landscape—i.e., in remote areas with steeper slopes—the predicted disturbance probability may be higher on national forest land. Again, this is consistent with a multiple-use strategy that spreads out harvest activities over the landscape.

To our knowledge, the only other studies that compare harvesting behavior by ownership arc Newman and Wear [1993] and Jackson [1987]. The former compares timber supply and investment decisions by industrial and nonindustrial private landowners in the U.S. Southeast and therefore provides no directly relevant insights for this study. The latter study compares timber (stumpage) prices received for National Forest and State forest timber sales in Montana (state timber is managed from trust lands with an emphasis on profitability). Jackson finds that prices paid for National Forest timber are substantially lower than those paid for state timber due in large part to the complexity and larger size of National Forest timber sales. While not directly comparable—the studies focus on different variables for comparisons these results are consistent with our findings of no correspondence between attributes that influence costs and the likelihood of harvesting. That is, an indifference to spatial factors---at least in the context of logging and transportation costs—should reduce stumpage values.

6. Mapping disturbance probabilities. In addition to providing a way to compare the harvest decisions of different owners, the methods used in this study could be used directly by public forest managers to estimate the potential volatility of neighboring private lands. This should be of increasing importance as public forest managers focus more on ecological services that depend on spatial configurations of habitat and cover. Because the relevant configurations do not respect ownership boundaries, public plans may increasingly need to be evaluated in the context of existing and expected conditions on neighboring private lands.

One way to estimate the potential for change on private lands is to apply the model of disturbance probabilities defined by equation (4) to existing conditions on private lands. This is a straightforward application with a Geographic Information System. First, the values for all independent variables in X_j are defined for each cell. Then these values are applied to equation (4) to estimate the predicted probability of disturbance for each cell. A map of these predicted harvest probabilities can then be generated and used to identify where private disturbance probabilities are likely to be relatively low or high.

Consider, as an example, the harvest probability map for private land in Macon County shown in Figure 2. This was derived using map layers in the GIS for Macon County and the estimates of equation (4) shown in Table 2. All private land that was not in forest cover in 1986 is unshaded and national forest land is identified. The remainder of the landscape was private forest in 1986 and is shaded from light to dark

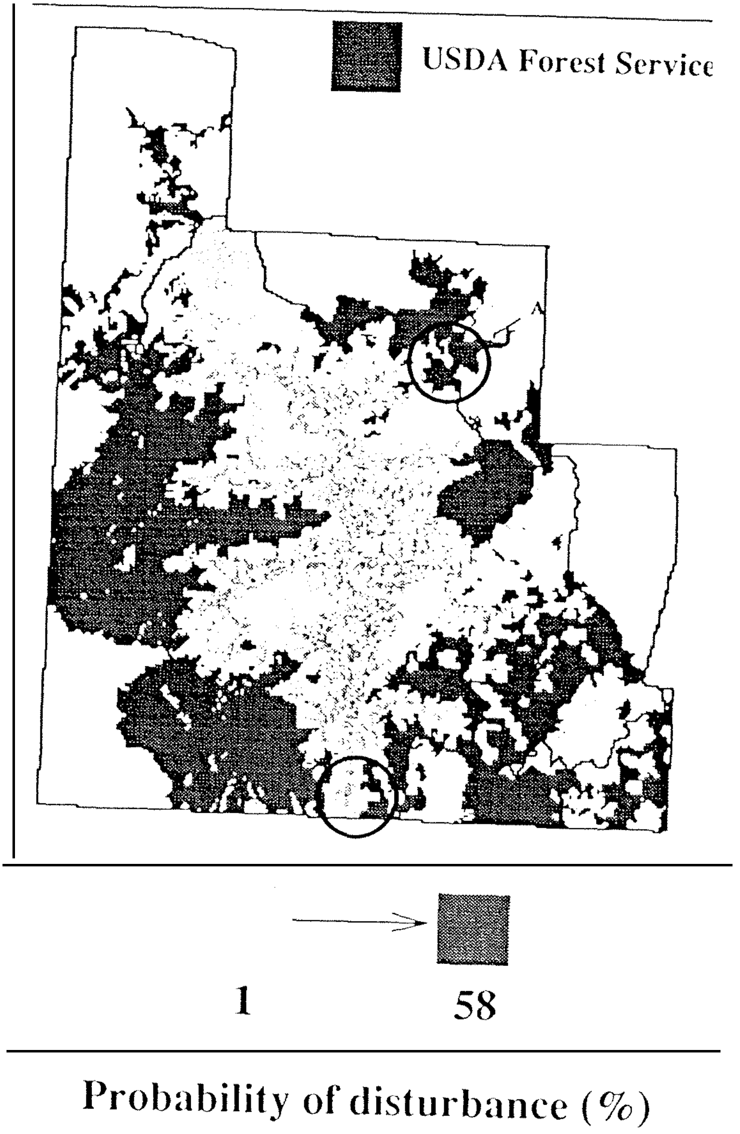

FIGURE 2. Predicted probabilities of forest disturbance on private lands for the Macon County study area.

grey to represent increasing probability of disturbance.

Figure 2 highlights where the national forest is adjacent to potentially volntilc private lands. For example, the two circles on the map marked A and B identify areas where national forest land is intermingled with private land that, has a relatively high probability Of disturbance. In these arms, forest managers might., for example, seek to emphasize the connectivity Of habitats--- that is, to act as a buffer against further habitat, fragmentation caused by harvesting private forests. Managers might, also use this type of information to t arget harvesting in areas where there was a deficit of existing and anticipated edge habitats. In general, where species demand a combinat ion Of habit at. condit ions, some Of which may be scarce on private land, t he scarce conditions could be provided On public land.

Clearly this example is simple and conject ural. However, it points t 0 the potent ial usefulness Of spat ially explicit informat ion on private lands for managing public lands. The application Of timber harvest models and, more generally, land use decision models, to Geographic Information Systems could provide a tool for evaluating public land management in the broader context of a mult iple ownership landscape.

7. Concluding **remarks.** Landscape dynamics are largely driven by human actors and their instit ut ions. Human act ivit ies clearly dominate the condition of land on our study site in the Southern Appalachians, and our decision models helped to explain harvest decisions by privat e landowners. They also provide a mechanism for comparing landscape dynamics on public and private lands.

Model estimates indicate that., on private land, all referenced locat ional variables significantly influenced dist urbance probabilit ies. No such relationships were found on the public lands. **Est** imates also allowed comparisons Of public and privat e disturbance probabilit ies. While overall probabilities were lower on public lands. they may exceed those on private land for some combinat ions of at t ributes.

Model est imates permit the landscape to be arrayed by t ho likelihood Of future dist urbance. Maps Of these values show where elements of the private landscape may be most volat ile. Because ecosyst em healt h oft en depends on t he configuration of forest condit ions across t he landscape, these types of models may be useful in ecosyst em management.

The models also may provide useful input, for simulation of landscape changes. To date, simulation models in the landscape ecology literature (e.g., Turner [1989]) have relied on raw empirical probabilities and *ad hoc* decision models to predict land cover changes.[5] Such applications do not account for the influence of land quality and location on the likelihood of land cover changes. These variables may have especially important effects in places where landscape conditions are highly variable. Methods developed here may help to improve the precision of landscape simulation models by incorporating the influence of land attributes on transition probabilities.

One potential extension of this approach is to the full complement of land cover and land use changes observed in our study site. Movements between forest and various agricultural uses as well as shifts between rural and urban or low-density residential uses of land could be studied. Such efforts would necessarily involve the simultaneous estimation of transition equations, perhaps using multinomial logit models (e.g., Maddala [1983]).

Future research could benefit from the compilation of additional data. Stand age data, which were not available for our study, could have improved the precision of forest disturbance models. The influences of other factors could also be examined within the framework of these models by extending the time series of land cover observations. This extension would allow the investigator to, for example, investigate the influence of changes in relative prices on land cover change.

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ENDNOTES

1. Most binary choice studies apply either the normal cdf (defining the Probit model) or the logistic cdf (defining the logit model). The logistic closely approximates the normal distribution and there is little theoretical imperative for selecting between the two (see Judge et al. [1985, p. 767]). However, we find a practical argument for using the logit. Its closed form (i.e., no integrals) allows for the direct calculation of predicted probabilities and therefore holds advantage for post-estimation analysis and mapping of disturbance probabilities.

2. The distance was calculated as the shortest route across the road network using an algorithm in the software package ARC-INFO.

3. The confidence interval is constructed as a normal deviate. Define the total pixels sampled for private and public lands as n_r and n_u, respectively, and the proportion of disturbed pixels as p_r and p_u. Then the confidence interval for the difference in means is given by:

$$p_r - p_u \pm z_{\alpha/2}\left[\frac{p_r(1-p_r)}{n_r} + \frac{p_u(1-p_u)}{n_u}\right]^{0.5}$$

where $z_{\alpha/2}$ is the normal deviate for the α percent confidence level.

4. Logit estimates (β) do not directly define the effects of marginal changes in the independent variables. Marginal effects are defined by taking the derivative of the cdf with respect to the individual variables. For example,

$$\frac{\partial F(X\beta)}{\partial X_k} = \frac{e^{X\beta}}{[1+e^{X\beta}]^2}\beta_k \tag{1}$$

where k refers to the kth independent variable.

5. An exception is Parks [1991]. He introduces land rents as explanatory variables of land use transitions for a landscape simulation model.

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