Policies to Reduce Forest Fragmentation: Combining Econometric Models with GIS-Based Landscape Simulations

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Abstract: Forest fragmentation is a primary threat to terrestrial biodiversity. We combine a parcel-level econometric model of land-use transitions with spatially-explicit landscape simulations to predict the empirical distribution of fragmentation outcomes under given market conditions and policy scenarios. Our model explains transitions between forest, agricultural, and urban uses, allowing us to model land use change in both rural and urban areas. A Monte Carlo simulation approach links econometrically-derived transition probabilities to GIS maps for the prediction of the spatial properties of habitat change. (JEL: Q240, Q570)

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David J. Lewis and Andrew J. Plantinga[1]

I. Introduction

Human-induced land use conversion is one of the primary determinants of environmental change worldwide. A typical consequence of forestland conversions is the fragmentation of the original forest base. Fragmentation occurs when an originally contiguous patch of forestland becomes separated into several disjunct patches. Forest fragmentation has long been considered a primary threat to terrestrial biodiversity (Armsworth et al. 2004). In the United States, the population decline of many species of birds is one example of a potential loss of biodiversity. According to one recent estimate, approximately twenty percent of the bird species in the U.S. have declined significantly in population over recent years (National Audubon Society 2002). While there are many potential causes of declines in U.S. bird populations, one primary cause is thought to be the fragmentation of forested habitat (Askins 2002; Faaborg 2002), particularly along the eastern seaboard and in the Midwest region.

A recent GIS analysis of the fragmentation of continental U.S. forests indicates that most forested parcels in the lower 48 states are found in fragmented landscapes (Ritters et al. 2002). Heavily fragmented landscapes have fewer interior parcels; i.e., forested parcels that are a certain minimum distance from the nearest edge. Such interior

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parcels provide the best habitat for many sensitive species (Robbins et al. 1989, Robinson et al. 1995, Askins 2002). For example, some species of interior-forest songbirds require habitat that is more than 200m from the nearest non-forest edge (Temple and Cary 1988). However, approximately 62% of forest in the lower 48 states is located within 150m of the nearest edge, which suggests that fragmentation of U.S. forests is so pervasive that edge effects influence ecological processes on most forested lands (Ritters et al. 2002).

The purpose of this paper is to develop a methodology for accurately predicting the spatial structure of landscape change under given market conditions and policy scenarios. The geography literature has devoted much attention to the use of GIS-based simulation techniques (notably cellular automata) in predicting landscape change (Clarke and Gaydos 1998; Wu 1998, 2002), but relatively little to the underlying behavioral factors affecting landowner decisions or the influence of market conditions. Conversely, the economics literature has devoted much attention to estimating behavioral models of landowner decisions (e.g. Stavins and Jaffe 1990; Bockstael 1996; Cropper et al. 2001), but less to the application of these models to predicting the future spatial pattern of the landscape. Our approach has two main components. First, a behavioral model of land use conversion is estimated at the parcel level to provide land use transition probabilities that are a function of market-based returns and the physical characteristics of the landscape. Second, we use simulations to relate the transition probabilities to actual landscapes so that the future spatial patterns of the landscape can be predicted.

Our work is distinguished from the empirical literature on spatial land use in two ways. First, this is the first paper designed to explicitly analyze the effect of land-use policies on habitat fragmentation across a large landscape. The consequences of fragmentation for biodiversity loss highlights the importance of land use analyses which focus on the spatial pattern of wildlife habitat. Second, this is the first paper to utilize a monte carlo simulation approach in the application of econometrically-derived land use transition probabilities to GIS maps of actual landscapes. Other papers (Nelson et al. 2001; Irwin and Bockstael 2002) apply transition probabilties as deterministic rules, which typically involve converting parcels of land to the use with the highest econometrically-derived transition probability, regardless of its magnitude relative to the probability of other land uses[2]. A consequence of such a methodology is the prediction of a single landscape. However, utilizing probabilities in such a way treats them as deterministic rules and is inconsistent with the purpose of specifying choice probabilities. By specifying choice probabilties, the researcher is saying that if the choice situation were repeated numerous times, each alternative would be chosen a certain proportion of the time (Train 2003 p. 73). In this paper, we simulate multiple landscape configurations which satisfy the underlying probability rules but which do not assume that parcels always convert to the use with the highest probability. To analyze the spatial patterns of the predicted landscapes we calculate fragmentation indices developed in the landscape ecology literature after each simulation and present a distribution of fragmentation outcomes.

The focus of our analysis will be on the coastal plain of South Carolina (Figure 1). This region was chosen for four primary reasons. First, approximately 83% of the landscape is privately-owned and can be classified as either forest, agriculture, or urban. Thus, our profit-maximizing land-use conversion model will be appropriate at explaining landscape change on the coastal plain. Second, this is a region of conservation concern. A

[2] Irwin and Bockstael (2002) apply urban development probabilities to undeveloped parcels with multiple rounds of development. In each round, the parcel with the highest probability of conversion is the parcel chosen for conversion.

bird conservation plan developed by Partners in Flight identifies approximately 22% of the region's bird species as a high conservation priority. Among the primary conservation goals in the Partners in Flight plan (as in many other wildlife conservation plans), is the provision of large blocks of un-fragmented contiguous forest habitat. Third, there is significant spatial heterogeneity in initial land uses across the coastal plain. Forestland makes up approximately 57% of this landscape and is fragmented in varying degrees by both agriculture (21% of the landscape) and urban (5% of the landscape) land uses. Figure 1 shows the distribution of forestland and core forestland (a measure of fragmentation) across the coastal plain. Such spatial heterogeneity will allow us to analyze the effects of initial landscape conditions on predictions of fragmentation in both urban and rural areas. Lastly, the South Carolina Department of Natural Resources has compiled a comprehensive natural resources GIS database which is amenable to the analysis we conduct.

II. Econometric Model of Land Use Change

Stavins and Jaffe (1990) solve a landowner's profit-maximizing dynamic optimization problem to determine a land-use transition rule. According to this rule, the landowner will convert to the use that yields the highest expected present discounted value of an infinite stream of net returns minus conversion costs. Following Lubowski (2002), we assume that landowners base their expectations of future land-use returns on current and historical land-use returns. In particular, we assume that landowners expect future land-use net returns to equal the average of the net returns over the five most recent years. We also assume that landowners ignore option values. With static expectations and no option values, the landowner's decision rule is to choose the land use with the highest expected one-period net return at time t. In formal terms, a landowner will convert from use j to use k in time t if the following holds:

$$R_{kt} - rC_{jkt} > R_{jt} \quad (1)$$

for all alternatives k. In this framework, R represents returns, r represents the discount rate, and C represents conversion costs. The landowner's profit function can be expressed as an indirect random utility function by writing the observed and unobserved portions of utility. Specifying the one-period net utility to the landowner on parcel i from switching from use j to k in time t:

$$U_{ijkt} = R_{ikt} - rC_{ijkt_t} = \beta_{jkt} x_{ijkt} + \varepsilon_{ijkt} \quad (2)$$

where x_{ijkt} is a vector of observed variables, β_{jkt} are parameters that are allowed to vary over time and over transition, and ε is a random error term. We can therefore define the probability that the owner of parcel i in use j will convert to use k during time t as:

$$pr(\beta_{jk_t}' x_{ijkt} - \beta_{jk_t}' x_{ijlt} \geq \varepsilon_{ijlt} - \varepsilon_{ijkt}) \quad (3)$$

for uses j=1,….,J. If we assume that the error terms are IID Type I extreme value, equation (4) yields a conditional logit model[3] with the following probability that parcel i changes from use j to use k between t and t+1:

$$P_{ijkt} = \frac{\exp(\beta_{jk_t}' x_{ijkt})}{\sum_{l=1}^{J} \exp(\beta_{jk_t}' x_{ijlt})} \quad (4)$$

P_{ijkt} embodies the first-order Markov property, because the probability of the parcel changing use depends only on decision variables in time t. In addition, the specification of choice probabilities as (4) implies an assumption of independence of irrelevant alternatives (IIA). The IIA property is a well-known assumption of logit models and

[3] Other assumptions regarding the error term produce alternative probabilistic models.

implies that the probabilities of any two choices must be independent of the other alternatives in the choice set. We provide test results below that fail to reject IIA as a null hypothesis. The elements of x include attributes of the different land use choices as well as attributes of the individual land parcels.

In addition to net returns, the literature has shown land-use conversion to be a function of soil quality (Plantinga 1996; Nelson et al. 2001), distance to urban areas (Kline and Alig 2001), and spatial interactions between plots (Irwin and Bockstael 2002). However, the discrete choice econometrics literature has not advanced enough to control for spatial autocorrelation, and thus an unbiased estimate of the spatial interaction effect is still not possible (Irwin and Bockstael 2002). With these considerations, we choose to specify land-use choice as a function of net returns to alternative land uses, soil quality, and urban influence. The following specification is used for landowner utility of switching parcel i from use j to use k, in county c, during time period t:

$$U_{icjkt} = \alpha^0_{jkt} + \alpha^u_{jkt} UI_i + \beta^0_{jkt} R_{kc} + \beta^q_{jkt} LCC^q_{it} R_{kc} + \varepsilon_{ijkt} \tag{5}$$

where α^0_{jkt} is an alternative-specific constant, α_{jkt} and β_{jkt} are parameters, R_{kc} denotes county-level returns to use k, UI_i is a dummy variable indicating whether the parcel is in a rural (1) or urban (0) area, and LCC^q_{it} is a dummy variable indicating whether plot i is in soil quality q at time t. Since net returns to land use are measured at the county level (see below), we interact these returns with plot-specific measures of soil quality to scale the returns up or down depending on soil quality. The parameter α^u_{jkt} is assumed to be zero for k = forest and k=agriculture, while β^q_{jkt} is assumed to be zero for k = urban[4]. For

[4] A likelihood ratio test fails to reject the null that $\beta^q_{jkt} = 0$ where k = urban at the 5% level.

identification, we normalize the alternative specific constants to be zero for the starting use. Costs-of-conversion from (1) will be captured in the alternative-specific constants.

Given the above normalization, we expect the alternative specific constants to be negative relative to starting use. This would signify that conversion costs are positive. The α^{u}_{jkt} coefficient is expected to be negative, which would scale down the probability of a plot converting to an urban use in a rural area versus an urban area. The β_{jkt}'s are expected to be positive, indicating that higher returns to a use increases the likelihood that it will be chosen as the ending use. The $\beta^{q}{}_{jkt}$'s are expected to be negative for the agriculture ending use (k = agriculture), indicating a lower probability of land converting to agriculture on lower quality land. The $\beta^{q}{}_{jkt}$'s are expected to be positive for the forest ending use (k = forest), indicating a higher probability of land converting to or remaining in forest on low quality land.

Land use data for this paper is derived from the National Resources Inventory (NRI), provided by the U.S. Department of Agriculture. To estimate parameters specific to the southeast region, we utilize data for the states of North and South Carolina. The NRI is a panel survey of land use, land cover, and soil characteristics that is conducted at five year intervals from 1982 to 1997 on a sample of non-federal lands across the U.S. Thus, there are 3 parcel-level land-use transitions observed here, each for a 5 year interval. The analysis in this paper is focused on lands that can be classified either as agriculture, forest, or urban uses. The remainder of the land base is classified predominantly as either water or federal land. Management of these lands is assumed not to be governed by profit maximization and they are excluded from the analysis. Land use returns are taken from Ruben Lubowski's (2002) national-level dataset. Annual county-level net returns are calculated by averaging the previous five years net return for each NRI starting period for the three land uses considered here (agriculture, forestry, and urban). The agriculture category is comprised of those lands classified as either crop or pasture land in order to match the econometric model to the available GIS data.

The NRI dataset includes information on the soil quality of each NRI plot. We utilize the land capability class (LCC) rating of each plot to scale the county-level returns for agriculture and forestry. LCC is a composite index representing many factors (i.e. soil type, slope, etc.) important to the suitability of the land for agriculture. The LCC index ranges from 1 to 8. To ensure sufficient observations in each group, LCC is placed into different groupings. For lands starting in agriculture, LCC is split into three different groupings: LCC 1 or 2, LCC 3 or 4, and LCC 5, 6, 7 or 8, with dummy variables indicating whether the parcel has a particular LCC ranking. For lands starting in forest, LCC is split into four different groupings: LCC 1 or 2, LCC 3 or 4, LCC 5 or 6, and LCC 7 or 8. We also utilize information on the urban status of the plot as defined by USDA's Economic Research Service (ERS). Each NRI plot is classified as urban-influenced or not urban-influenced based on an index of urban proximity derived from Census-tract population data from 1990[5]. The derived index is similar to a gravity index, and provides a measure of accessibility to population concentrations. The linking of this index to NRI plots is particularly useful because the only other location information disclosed on the NRI plots is the county in which they reside.

The NRI provides a panel data set with three 5 year transition periods observed (1982-87; 1987-92; 1992-97). However, panel data estimation is infeasible with a logit

[5] We thank Vince Breneman at ERS for linking urban influence to the NRI plots and Shawn Buckholtz at ERS for providing the corresponding GIS layer on urban influence.

model unless we are willing to assume that unobserved components of utility are uncorrelated over time. There are many unobserved elements of utility (e.g. distance to major roads) which will clearly be correlated over time for particular parcels. Thus, to maximize variation in the dataset and to ensure efficient estimation, we utilize a pooling strategy which provides some of the benefits of panel data estimation without adding the above restrictive assumption[6]. Lastly, we weight the observations with the NRI's acreage weights in order to ensure that the sample is representative of the population[7].

Results

The econometric model is estimated using maximum likelihood procedures for the pooled sample. Results are presented in table 1. The parameters are estimated separately for each of the two starting land uses (agriculture and forest). Lands beginning in an urban use are assumed not to leave urban. There are 9,692 observations in the sample with agriculture as the starting land use, and 20,721 observations for the sample with forest as the starting land use. Likelihood ratio tests reject the hypothesis that all of the coefficients are simultaneously equal to zero (0.01 level) for each of the equations. In addition, pseudo R^2 is approximately 0.8 for land uses starting in agriculture and 0.9 for land uses starting in forest, indicating that the specified model increases the log-likelihood function above the value taken at zero parameters. Thus, the estimation results suggest a good model fit for both starting uses. Hausman tests for independence of

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[6] For land parcels that remain in a given land use for all three periods, we randomly select one-third of the parcels from each time period. For parcels that are in a given land use at the start of only two periods, we randomly select one-half of the parcels from each period. For parcels that are only in a particular use at the start of one of the periods, we include all of the observations. The observations are then weighted 3,2, and 1, respectively, to those parcels that were sampled at 1/3, ½, and 1/1 intensity.

[7] Each NRI point is given an acreage expansion factor between 1 and 192, with lower numbers indicating a lower acreage weighting and a more intensively sampled region. To avoid shrinking standard errors due to this weighting, the weights are scaled so that they sum to the total number of actual observations.

irrelevant alternatives (IIA) were run for both starting uses with results failing to reject a null hypothesis of IIA at the 0.05 level for each of the two starting uses[8].

The alternative specific constants are negative and significantly different from zero at the 1% level, suggesting that conversion costs are an important component in a landowner's land use decision. Likewise, coefficients on the alternative-specific returns are all positive and significantly different from zero at the 1% level. This suggests that higher net returns to particular land uses increase the probability that these land uses will be chosen. In terms of the coefficients interacting net returns with soil quality, all are correctly signed and 5 of the 9 coefficients are significantly different from zero at the 10% level or higher, while 4 of the 5 significant coefficients are significantly different from zero at the 5% level or higher. This suggests that soil quality is an important component influencing land use transitions. For parcels starting in agriculture, coefficients indicate that parcels with lower soil quality will be less likely to stay in agriculture and more likely to convert to forest or urban uses. For parcels starting in forest, coefficients indicate that parcels with lower soil quality will be more likely to stay in forest and less likely to convert to forest or urban uses. Lastly, the coefficient on the urban status of the plot is negative and significantly different from zero at the 1% level, indicating that parcels in rural areas are less likely to convert to urban uses than parcels in urban areas, ceteris paribus.

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[8] Since the Hausman test is of low power, we also evaluate the conditional logit model against the Heteroscedastic Extreme Value (HEV) model, which doesn't impose IIA. The results are mixed. For the forest starting use, a likelihood ratio test fails to reject the conditional logit model in favor of the HEV model at any reasonable confidence level. For the agriculture starting use, a likelihood ratio test rejects the conditional logit model in favor of the HEV model. However, the scale parameter coefficients in the HEV model are not significantly different from each other at the 5% level, which is not evidence against IIA. Thus, comparison of the HEV and conditional logit models offers no firm rejection of IIA as a null hypothesis, confirming the Hausman test results.

Of primary importance for the landscape simulations in this paper are the spatial properties of the transition probabilities. The probabilities are differentiated spatially by starting land use, county-level returns to alternative land uses, parcel-specific soil quality, and urban status (as defined by USDA's urban influence index) of the parcel. For lands starting in agriculture, the probability of leaving agriculture for forest or urban uses increases as soil quality decreases. In addition, the probability of agricultural parcels converting to urban uses is significantly higher in urban areas than in rural areas. In contrast, for lands starting in forest, the probability of leaving forest for agriculture or urban uses decreases as soil quality decreases. Similar to lands starting in agriculture, the probability of forest parcels converting to urban uses is significantly higher in urban areas than in rural areas.

III. Landscape Simulation Methodology

GIS Data Description

The GIS data for this project is derived from the South Carolina Department of Natural Resources' (SCDNR) GIS data clearinghouse. This is an integrated statewide natural resources database designed to facilitate natural resource decision making in South Carolina. We utilize GIS layers on land use, soil quality, public lands, urban influence, and political boundaries. The data are organized by quadrangles (quads), as defined by the U.S. Geological Service (USGS), resulting in 566 maps within the state. Each quad covers approximately 40,000 acres of land. In this study, we focus on the 295 maps comprising the coastal plain in the eastern half of the state. The land use data were developed by SCDNR in conjunction with the National Wetlands Inventory (NWI), conducted by the U.S. Fish & Wildlife Service. The land use data is delineated from 1:40,000 scale infrared photography (from 1989) and upland land use is categorized by the Anderson Level II system as designed by the U.S. Geological Service (USGS). The land use data is in vector format at 10 acre minimum resolution.

The soil quality layer is derived from existing county surveys available from the Natural Resources Conservation Service (NRCS). The data was digitized by SCDNR and linked to STATSGO tables of soil attributes, which characterize various soil quality measures. To match the soils layer with our econometric model we further linked these tables to USDA's SSURGO soils tables to obtain land capability class (LCC) information on each parcel. We also utilized GIS layers on public lands status as available from the SCDNR database. Each parcel was categorized as either private or publicly owned. Publicly owned lands include national forests, national wildlife refuges, state parks, state forests, and state-owned wildlife management areas. Lastly, we utilized a GIS layer of urban influence status from ERS to match each parcel with its urban status (defined with 2000 Census data). Thus, each parcel in the landscape is identified by land use category (agriculture, forest, urban, or water/missing), soil quality (LCC), public land status, and urban influenced status. The resulting GIS layer allows us to match the econometric land use model to the landscape for forecasting land use change. After overlaying all of the above layers, we end up with an average of approximately 7,500 parcels per quad, with the number being lower for those quads covering the immediate coastline. These quads typically have a significant portion of their area as water, which is counted as one 'parcel' in the GIS map. This gives us an average land parcel size of just over 5 acres.

Simulation Strategy

The econometric land use model provides transition probabilities specific to starting land use, soil quality, county-level net returns to various land uses, and the urban status of the plot as defined by USDA's urban influence index. Thus, each county will have as many as 42 separate transition probabilities, depending on the initial configuration of the land uses, soil quality, and spatial extent of the urban influence index. Thus, we assume that a common set of probabilities apply to all parcels of a given quality within a county. For example, two privately-owned agricultural parcels in a county that have identical soil quality and urban status will have the same probabilities of either remaining in or converting out of agriculture. We are thus assuming that key economic factors that determine transition probabilities (e.g., commodity prices) exhibit little variation within a county.

For the purpose of the simulations, one can view the estimated transition probabilities as a set of rules that govern land-use changes within a county. For example, if the value of the agriculture-to-forest transition probability is 0.10 for a particular quality parcel, an agricultural landowner of such quality land should convert their parcel to forestland about 10% of the time, if the same choice situation were repeated numerous times. Thus, the role of the simulations is to use random number generators to repeat the choice situation many times for each parcel in the landscape. Only privately-owned agriculture and forest parcels are assumed to transition, as urban land is expected to stay in urban status and water and public lands are not assumed to transition.

Fragmentation Indices and Number of Simulations

One consequence in our use of Monte Carlo simulations is that we cannot generate one particular landscape outcome. Instead we generate many possible landscape outcomes which all represent a different landscape which satisfies the underlying transition model. In order to analyze such a large set of spatial outcomes we calculate fragmentation indices for each simulation run. Of course, this brings up the issue of deciding which of many indices to use. To answer this question, we follow Ritters et al. (1995) and perform a principal components analysis (PCA) to reduce the number of calculated fragmentation indices. This is a method used extensively in the landscape ecology literature.

The PCA was run with the initial landscape of 295 quadrangles. A total of 32 fragmentation indices were calculated using the software Fragstats for each of the 295 quadrangles in rasterized form. Metrics were chosen to represent the following categories of landscape pattern: area, edge, shape, core area, isolation/proximity, contrast, contagion, interspersion, and connectivity. Results of the PCA indicate that approximately 84% of the variation in the larger set of indices can be captured with the use of only five indices. The first index is the percentage of the landscape in core forest (CORE). This index is calculated by totaling all forestland that is at least 200m from the nearest non-forest edge and dividing by the total area of the quad. The second index is the mean of the shape index (SHAPE), which is calculated for each forest patch in each quad. This index equals one when the patch is maximally compact and increases as patch shape becomes more irregular. The third index is the clumpiness index (CLUMPY), a measure of contagion, or the extent to which parcels of similar use are aggregated. This index ranges between -1 and 1 and equals zero when the focal patch type is distributed randomly. The fourth index is the splitting index (SPLIT), an index of habitat area and subdivision. This index equals one when the quad consists of a single patch, and increases as the focal patch type is reduced in area and/or becomes subdivided. The last index is average patch size (PATCH). This is a commonly used fragmentation statistic that averages the area (in hectares) of all patches in the quad. Detailed descriptions of these indices can be found in McGarigal et al. (2002).

By repeatedly simulating land-use transitions, we generate a distribution of potential fragmentation outcomes. One important question in Monte Carlo simulation is how many simulations is enough? The computational challenges inherent in this analysis preclude us from implementing a convergence rule which allows us to stop simulating once a particular criterion is met. Thus, we utilize a different strategy and select 5 representative quads to analyze the number of simulations required for the distributions to converge[9].

In considering the question of when to stop simulating data, Ross (1997) suggests an approach that considers the length of the confidence interval of the parameter of interest Θ(F) from the distribution F[10]. For the purposes of this study, we wish to characterize the first three moments of the distribution of fragmentation outcomes. Confidence interval lengths for the first three moments decrease at a decreasing rate with the number of simulations. Each interval length changes very little once 500 simulations

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[9] Representative quads were chosen along two axes: the expected change in a quad's forest habitat as defined by the econometric model, and the amount of initial fragmentation on the quad.

[10] Additional simulations are run until the approximate 100(1-α) percent confidence interval estimate of Θ is less than some chosen length l. The researcher's job is to choose the parameter of interest Θ(F), as well as α and l accordingly.

have been run[11]. To further investigate whether 500 simulations adequately characterize the distributions, we run an additional test. In particular, we hypothesize that if 500 simulations is enough, then the estimates of the first three moments should not be statistically different between two separate samples of 500 simulations. Results confirm that the estimates of the first three moments are not statistically different from each other at the 1% level across two simulated samples. We interpret these results as evidence that 500 simulations is an adequate number of simulations to characterize the distribution of fragmentation outcomes across the representative quads.

IV. Landscape Simulation Results

Baseline results (with constant relative net returns to land) were simulated for a 30 year time horizon for all 295 individual quads across the landscape. Computing time is an issue with this analysis as the average quad has approximately 7500 parcels of land with which to apply the simulations. It takes roughly 295 hours (or 1 hour per quad) to simulate 500 landscape outcomes for each quad and do the respective fragmentation calculations. This equates to roughly 12.3 days of computing time. The results consist of distributions of the various fragmentation indices for each quad, rather than one single landscape outcome.

In order to understand the effects of the underlying spatial heterogeneity of each landscape on the baseline simulations, we select three quads with almost identical first moments of the core forest index and examine the differences in their distributions. Figure 2 presents the empirical probability distributions from each of these quads for the core forest index. Each of the three quads has a mean of the core forest index at approximately 39% of the landscape. However, the second and third moments of the

[11] We use bootstrapping to estimate standard errors for the estimators of the second and third moments.

distributions are quite different from one another. In particular, the Gadsden quad has a much smaller variance and is much more symmetric than the distributions for the other two quads. The distribution of the core forest index for the Grays quad has a much higher variance and is much more skewed than the other distributions. The distribution from the Snow Island quad falls in between the other two in terms of variance and skewness. Of particular interest is that even though all three quads are predicted to have similar means in the core forest index (~39%), the probability of being well away from the mean is significantly different across quads. In particular, the empirical distribution functions indicate that the probability of having greater than 43% of the quad in core forest is 0.2 for the Grays quad and 0.03 or less for the other two. Likewise, the probability of having less than 35% of the quad in core forest is 0.12 for the Snow Island quad, 0.08 for the Grays quad, and 0 for the Gadsden quad.

All three quads are heavily forested initially, with the Grays and Gadsden quads being roughly 80% forested and the Snow Island quad being 90% forested. However, 28% of the Gadsden quad is in public ownership, and thus not expected to transition. In contrast, the Grays and Snow Island quads are almost entirely in private ownership and thus subject to land use conversion, a fact which may partially explain the increased variance in the distributions of these quads. Interestingly, the Gadsden quad is the only one of the three with any urban influence, and yet this is the quad with the tightest distribution of core forest around the mean. The important point to consider is that three landscapes with similar aggregate levels in land use and similar predictions of the mean of fragmentation outcomes can still have very different distributions of those same outcomes. This highlights the role that the spatial heterogeneity of the initial landscape can have on the probability of particular fragmentation outcomes.

In order to understand expected changes in fragmentation across the entire coastal plain, we also focus on the changes expected in each index relative to the initial landscape, where changes will be evaluated at the means of the forecasted distributions. The most basic result to look at is the change in total forest cover. The statistic used is the percentage of each quad in forest, and 82 of the 295 quads (28%) are forecast to increase their forest cover while 213 of the 295 quads (72%) are forecast to have decreases in forest cover in the baseline. The range is from a maximum loss in forest of over 19 percentage points to a gain of just over 10 percentage points. Most of the increases in forest cover come in the western part of the coastal plain, which is the more agricultural region. The largest decreases in forest come in the more urban-rural fringe areas, particularly those near the coast around Charleston.

For fragmentation, we first focus on changes in the percentage of each quad in core forest. Only 2 of the 295 quads (less than 1%) are forecast to have any increases in core forest, with the remaining 293 quads (over 99%) predicted to have decreases in core forest (Figure 3). The range in this statistic is from a maximum loss in core forest of almost 43 percentage points to a gain of 0.25 percentage points. In general, areas with higher losses in total forest cover are also the areas that are forecast to have higher losses in core forest; the difference is in the magnitude. The loss in the percentage of the landscape in core forest greatly exceeds the loss in the percentage in forest in many of the quads. This is suggestive of significant decreases in core forest beyond decreases in total forestland.

The second fragmentation statistic analyzed is the change in average forest patch size. This statistic yields a more complex picture of future fragmentation patterns across the region. Of the 295 quads, 259 (88%) are predicted to have losses in their average forest patch sizes, while 36 (12%) are predicted to have gains in their average forest patch sizes (Figure 3). The results range from a maximum decline in average patch size of 85% to a maximum increase of 48% over the initial average patch size. Most of the gains in average patch size come in the agricultural region of the coastal plain. Interestingly, the gains in average patch size come in areas that are either predicted to lose core forest or to have virtually no change in core forest. This suggests that it is mostly edge forest that is forecast to be added in this part of the coastal plain rather than core forest.

The magnitudes of the other indices are more difficult to interpret, and so we only focus on whether predicted changes in these indices yield a more or less fragmented landscape. Results from changes in the splitting index indicate that 209 of the 295 quads (71%) are getting more fragmented (increases in the index) and 86 (29%) quads are becoming less fragmented. Predicted changes in the clumpiness index indicate that 290 (98%) are getting more fragmented (decreases in the index) and 5 (2%) are getting less fragmented. Lastly, predicted changes in the mean of the shape index indicate that only 116 (39%) quads are predicted to get more fragmented (increase in the index) while 179 (61%) are predicted to get less fragmented[12].

V. Conclusions and Next Steps

This paper has integrated a behavioral econometric model of land use conversion with spatially-explicit landscape simulations to forecast changes in forest fragmentation

[12] A GIS map of these fragmentation indices was not reported here but is available from the authors upon request.

across the coastal plain of South Carolina. A parcel-level econometric model was specified to predict changes between forest, agricultural, and urban uses. Results highlight that such a model is necessary for analyzing fragmentation because of the many channels with which land use change operates. In particular, while forest lands are predictably expected to become more fragmented in the urban-rural fringe, afforestation in some rural agricultural areas actually increases the average forest patch size and decreases fragmentation in those areas. Thus, a complete understanding of fragmentation across a large landscape requires the modeling of both urban development and transitions between agriculture and forestry.

Another important methodological issue is the application of econometrically derived transition probabilities to GIS maps. A Monte Carlo simulation methodology is introduced in this paper which extends the empirical land use literature by treating the econometric results as probabilistic transition rules rather than deterministic rules in the forecasting of the spatial structure of landscape change. The deterministic approach typically assigns parcels to the use with the highest predicted probability, resulting in one forecasted landscape rather than a distribution of possible landscapes, such as we present here. However, results in this paper highlight that the distribution of potential spatial outcomes can vary widely across landscapes, even when the first moments of the distributions are similar. A potentially interesting future application would be to compare the results of the two methodologies to determine where landscape outcomes predicted with deterministic rules would lie along the Monte Carlo distributions presented here. It is important to note that they would not necessarily lie at the mean of the distributions.

Baseline results presented here indicate that forest fragmentation is predicted to increase across much of the coastal plain of South Carolina, particularly in those areas most affected by urban development. But, some of the more rural, agricultural areas may actually have reductions in some indicators of fragmentation. However, reductions in fragmentation appear to be based on increases in forest patch size due to the addition of edge forest rather than the addition of core forest in these rural landscapes. Results here highlight the fact that forest fragmentation is affected by both urban development of forestland as well as transitions between the forest and agricultural sectors. The net effect of land use change on forest fragmentation is a result of the spatial location of those parcels leaving forest and the spatial location of those parcels entering forest. Regions with an active margin between agriculture and forestry may be able to mitigate somewhat the effects of urban development on forest fragmentation.

The results presented in this paper are preliminary and do not yet consider policy simulations. Our next steps include simulating various land use policies which alter the net returns of forestry relative to agriculture and urban uses. In addition, we plan to utilize the predicted fragmentation statistics in an ecological model to translate changes in forest habitat and fragmentation to changes in bird populations (e.g. Matthews et al. 2002). Finally, we plan to analyze the economic efficiency of various land use policies aimed at altering the spatial configuration of land.

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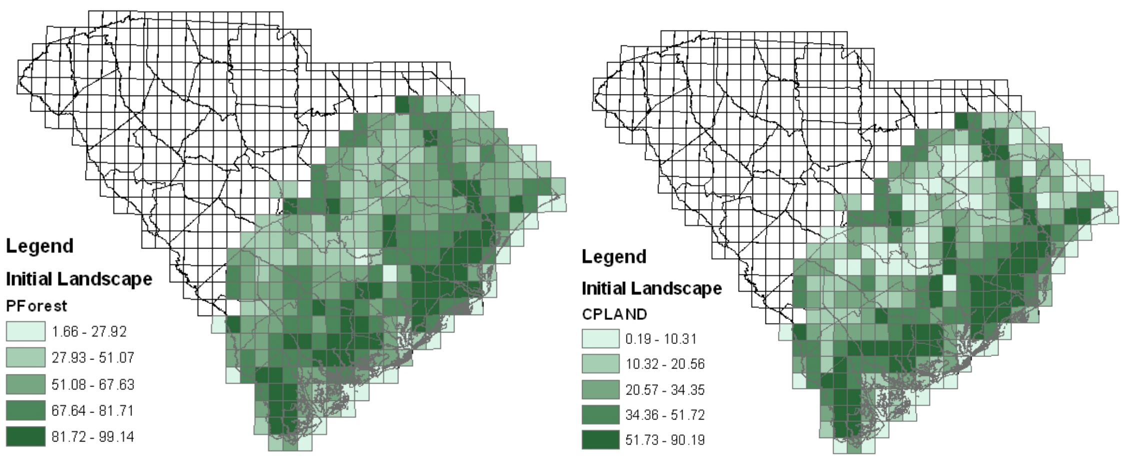
Table 1 – Econometric results for land use transition model

Parameter	Starting Use Agriculture	Forest
Ag Intercept		-4.7767**
		-(40.71)
Ag Returns	0.0033**	0.0056**
	(3.61)	(3.68)
Ag Returns *LCC 3 or 4	-0.0021	-0.0014
	-(1.69)	-(0.78)
Ag Returns *LCC 5,6,7, or 8	-0.0064**	0.0024
	-(3.93)	(1.12)
Forest Intercept	-4.0478**	
	-(34.73)	
Forest Returns	0.0535**	0.0210**
	(6.02)	(2.53)
Forest Returns * LCC 3 or 4	0.0024	0.0057
	(0.36)	(0.95)
Forest Returns * LCC 5 or 6		0.0313**
		(3.72)
Forest Returns * LCC 7 or 8		(0.06)**
		(5.97)
Forest Returns * LCC 5,6,7 or 8	0.0553**	
	(5.18)	
Urban Intercept	-3.6846**	-3.2724**
	-(33.11)	-(28.03)
Urban Influence (1 = rural, 0 = urban)	-1.3773**	-1.4068**
	-(12.53)	-(17.93)
Urban Returns	0.0003**	0.0002**
	(7.24)	(6.79)
Pseudo R^2	0.7942	0.8928
N	9692	20721

** Significant at the 1% level; * Significant at the 5% level
t statistics in parentheses

Figure 1 – Coastal Plain of South Carolina by USGS quadrangle (quads)

Percentage of Quads in Forest — Percentage of Quads in Core* Forest



* Core forest is defined as forest that is at least 200m from the nearest non-forest edge

Figure 2 – Distribution of Core Forest Index for Selected Quads

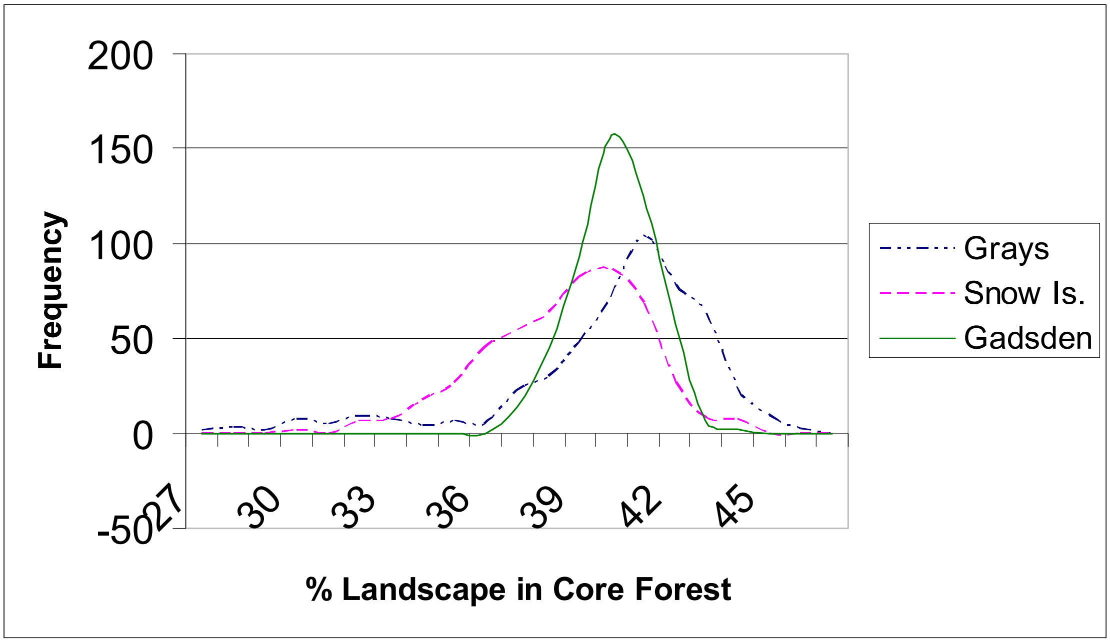


Figure 3 – Change in fragmentation indices (Baseline 30-yr horizon)