Effect of Urbanization on the Forest Land Use Change in Alabama: A Discrete Choice Approach

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Abstract

The study focuses on exploring the impacts of urbanization on changes in forest land use/land cover in Alabama for the period between 1972 and 2000. Nested logit analysis of the discrete land use choices made by the private landowners show that initial forest type and population gravity index significantly explain the variation in forest type transition. Anthropogenic factors influence the decision in favor of forest land conversion to non-forest use. Softwood stands were more preferred for harvests relative to hardwood while hardwood was the more preferred choice for maintaining land in forest cover near the population centers relative to softwood.

Key Words: nested logit, urbanization, land use, population gravity.

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Introduction

Land use change and respective change of land cover attributed to human activities on land is a common phenomenon associated with population growth, market development, technical and institutional innovation and policy action. Vitousek (1994) identified land cover changes by humans as the primary effect of humans on natural systems. Few forested areas on our planet have not been influenced by human actions, yet the effects of long-term human influences on land use/land cover changes from forestry are not well documented. Various models differing in temporal and spatial scales and quantitative techniques have been applied by researchers/scientists to uncover the determinants of land use change. A close look at past land use studies reveals that biophysical factors such as land quality and topography; economic factors such as population, market conditions, proximity to population centers and income; and institutional factors such as government policy are the major determinants of land use change. The objective of this paper is to explore the effect of increasing population pressures on choices made by the private forest landowners of Alabama. Alabama ranks second in the nation in acres of forestland (excluding Alaska), ((NRI, 1997) http://www.al.nrcs.usda.gov/technical/nri/97highlights.html) and the forests of the state account for 13% of the total timber removals in the South (Smith et al 2002). The impacts on forestry land use including changes to non-forest uses viz. agriculture and urban/developed land or changes in forest types (land cover changes) will have significant effects on the ability of Alabama’s forests to provide both timber and non-timber amenities in the future.

Literature Review

Empirical land use change models have been constructed using primarily two approaches. The first is the aggregated approach that models areas or proportions of land in different use categories such as forestry, agriculture and urban (Alig 1986, Hardie and Parks 1997) or different forest types such as softwood, mixed hardwood, hardwood, agriculture and urban land (Zhang et al 2005) within a well defined geographic region such as a county as a function of socioeconomic variables and land characteristics aggregated at the level of the geographic unit of observation. The second is the spatially explicit approach that explicitly models land use change on the basis of pixels, parcels, or sample points (Bockstael 1996, Chomitz and Gray 1996, Munn and Evans 1998, Wear and Bolstad 1998, Kline et al., 2001, Lubowski, 2002). While the aggregated approach has the disadvantage of averaging the physical land characteristics for the unit of study, the spatially explicit approach has often found it difficult to obtain spatial socio-demographic data at scales finer than the census tract level which are virtually nonexistent. Also in the former approach, the coefficients of the model capture simultaneously both the spatial and temporal effects and has done a poor job in projecting land use shares through time (Ahn et al., 2000). In contrast, the spatially explicit approach models the change directly by taking into account the dynamic nature of the land use change decision.

Empirical Land Use Model

Researchers have extensively used multinomial logit models (Chomitz and Gray 1996; Turner et al. 1996; Hardie and Parks 1997) for explaining landowners’ choice of land use without taking into consideration the possibility of correlation between alternative choices. A feature of our study is the use of the less restrictive nested logit econometric
framework which relaxes the assumption of Independent and Irrelevant Alternatives (IIA) \(^5\) to account for the possible substitution patterns amongst alternative choices. 

We employ a discrete choice approach to model the land use decision making behavior of private forest landowners. It is assumed that a landowner starting with an initial forest type chooses between the five possible discrete alternatives the one that maximizes his utility. The alternative choice set includes either converting forest into non-forest use, regenerating into one of the three forest types (hardwood, softwood or mixed) following harvest and a no harvest \(^6\) decision to maintain the initial forest type. A landowners’ utility gained from choosing a particular alternative depends on the attributes associated with each forest plot.

For models of land use change, the vector of plot characteristics, \(x\), typically consists of data on land quality, socio-demographic, socio-economic and rent (return) to alternative land use choices. In this discrete choice framework, a risk neutral landowner is assumed to choose for parcel \(i\) an alternative \(k\) from a set of \(J\) alternatives that maximizes his utility at time \(t\).\(^7\) Assume that the landowner’s utility function for choice \(j\) is given by:

\[
V(\beta_j, x) = v(\beta_j, x) + \epsilon_j
\]

where \(x\) is the vector of attributes of plot characteristics and \(\beta_j\) is a vector of preference parameters on the observable portion of the landowner’s utility function for the alternative \(j\), \(v(\beta_j, x)\). Finally, \(\epsilon_j\) is the unobservable portion of the landowner’s utility function and is assumed to be a function of certain forest plot characteristics and the characteristics of the decision maker. The landowner then compares all potential choices in his choice set ‘\(J\)’ and chooses the best land use alternative ‘\(j\)’ such that:

\[
V(\beta_j, x) > V(\beta_k, x) \quad \forall \quad j \in J, \quad k \in J, \quad k \neq j
\]

The challenge is to take the model given by (1) and (2) and develop a statistical model that will enable the recovery of the parameters \(\beta\). The structure of the model will depend heavily on the assumptions about the form of the distribution of error terms. Assuming error terms \(\epsilon_j\) are independent and identically distributed (i.i.d.) with a Type I Generalized Extreme Value distribution (GEV) \(^8\), (1) and (2) are expressed as a multinomial logit model:

\[
\text{Prob}(k) = \frac{\exp(\beta_k 'x)}{\sum_{j \in J} \exp(\beta_j 'x)}
\]

This denotes that the ratio of probabilities of choices \(k\) and \(j\) would remain unchanged with a change in the parameters of choices other than \(k\) and \(j\) (IIA). In reality, that might not be the case. For example, a change in the stumpage price of hardwood might influence the ratio of probabilities of transition to pine plantation vs. probability of transition to agricultural land. A study by Lubowski (2002) on the economic and policy determinants of land use change

\[^5\] McFadden (1973) suggested that IIA implies that conditional and multinomial logit models should only be used in cases where the outcome categories can plausibly be assumed to be distinct and weighed independently in the eyes of each decision maker.

\[^6\] This study does not assume type transition if there is no harvest and considers the forest type as fixed until harvest occurs.

\[^7\] For notational simplicity the subscripts \(i\) and \(t\) will be dropped from the equations.

\[^8\] Type I GEV also known as Gumbel distribution is based on simplifying assumptions such as independent and identical distribution (iid) of random components and the absence of heteroscedasticity and autocorrelation in the model (see Mcfadden (1974) for details).
using a nested logit model supports the need for exploring alternative nesting structures in land use studies. We use a three level nested logit model, which assumes that decisions are made at three hierarchical levels (Figure 1).

![Figure 1 Three level-nested representation of landowner decision](image)

The decision at each of these three levels is modeled as an outcome of separate utility maximizing decisions. The decision to harvest or not to harvest at the uppermost level of the nested tree can be modeled as a binary logit model. Assuming the landowner makes the decision to harvest, he has to make another decision at the medium level of the nested model, which is whether to keep the land in forest or convert it to non-forest use. This can also be modeled as a binary logit model. Finally, assuming the landowner decides to keep the land in forest use, he decides whether to regenerate it to a softwood, mixed or hardwood type of forest. Each of these decisions is taken with a view of maximizing utility. The three level nested model decomposes the choice probability into three components, the marginal probability of choosing a particular subgroup (nest) \( s \) at the uppermost level, \( S=1,2 \) for harvest or no harvest, the marginal probability of choosing a particular sub-nest \( l \) within the nest \( s \), where \( L=1,2 \) for non-forest or forest, and the conditional probability of choosing a particular alternative \( j \) at the lowest level within the alternative set \( J=1,...,J_{l,s} \) in the sub-nest \( l \) and nest \( s \) conditional on the choice of that sub-nest and nest. Given this, the probability that a landowner \( i \) is observed choosing alternative \( j \) at time \( t \) in the nested logit formulation requires the decomposition of the choice probability in (3) into three components: the marginal probability \( P_{is} \) of choosing a particular nest \( s \) (\( s=1,2 \)) and conditional probabilities \( P_{il|s} \) and \( P_{ij|ls} \) of choosing a particular sub-nest \( l \) (\( l=1,2 \)) conditional on the choice of that nest \( s \) and choosing a particular alternative \( j \) from within the alternatives (\( j=1,2,3,4,5 \)) conditional on the choice of that nest and sub-nest. The probability defined in (3) thus becomes:

\[
P_{adj} = P_{is} \times P_{il|s} \times P_{ij|ls} = \frac{\exp(\delta_s'y_i + \tau_s'x_{is}) \times \exp(\gamma_j'z_i + \sigma_{jls}'I_{ij}) \times \exp(\beta_j'x_i)}{\sum_{k \in S} \exp(\delta_k'y_i + \tau_k'I_{ik}) \times \sum_{m \in L} \exp(\gamma_m'z_i + \sigma_{mjl}'I_{jin}) \times \sum_{n \in J} \exp(\beta_n'x_i)}
\]

(5)

where \( \tau_s \) and \( \sigma_{jls} \) are the parameters associated with the Inclusive Value (IV) for nest \( s \) and sub-nest \( l \) defined as

\[
I_{is} = \ln \sum_{m \in L} \exp(\gamma_m'z_i + \sigma_{mjs}'I_{imin})
\]

(6)

and

\[
I_{jl} = \ln \sum_{n \in J} \exp(\beta_n'x_i)
\]

(7)
where, \( y_i \) are the observed plot attributes influencing the choice of the nest, \( z_i \) are the observed plot attributes influencing the choice of the sub-nest and \( x_i \) being the observed plot attributes influencing the decision to keep land in an alternative forest type conditional on the choice of the nest and sub-nest. The inclusive value for nest \( s \) and sub-nest \( l \) defined in (6) and (7) is the log of the denominator of the conditional probabilities in (5) and measures the average utilities of the alternatives within that subset of alternatives for the choice of a particular nest \( s \) and sub-nest \( l \). If the parameters \( \delta_k \) and \( \gamma_m \) are zero and the inclusive value parameters \( \tau_k, \sigma_{m/s} \) are jointly equal to one then the model will collapse into a multinomial logit model shown in (3).

### Data and Variables

The data for this study comes from the Forest Inventory and Analysis (FIA) program of the U. S. Department of Agriculture (USDA) Forest Service, USDA Economic Research Service (ERS), Bureau of Census and the Regional Economic Information System (REIS) of the Bureau of Economic Analysis (BEA). We used Alabama FIA data for the census years 1972, 1982, 1990 and 2000 and the Census Bureau data on population demographics for the same periods \([10]\). REIS provided us with the per capita personal income by county for the corresponding years. All the plots considered for the study were restricted to be in forest use at the beginning of the period and privately owned. The total number of observations for the period (1972-2000) of the study that consisted of three transition periods was 10383.

All the explanatory variables in the model, associated with the FIA plots were lagged values based on the previous period ‘t-1’ to incorporate the general trends in the variable’s effect on the landowners’ discrete choice as observed at the current period \( t \). For example a FIA plot observed in a particular land use for the FIA survey year 1982 had all the corresponding explanatory variables from the FIA survey 1972 and the population census for the year 1970 and so on. From among the array of variables used in this study the key variable that represents the influence of humans on forest land use change is the Population Gravity Index (PGI). The PGI was constructed by utilizing information on the location of the FIA plots in relation to the location of Census populated places within 100km. The geographic location of census places \([11]\) was taken from ESRI Data and Maps, 2005 (http://www.esri.com/data/about/data_maps_media.html). Other variables in the model include the initial forest type dummy for the three classes of forest type denoted by the variable names SW (softwood), MX (mixed) and HW (hardwood) for each FIA plot. Volume in cubic feet of all the trees within a FIA plot divided by the plot acres is denoted by \( VOL \) and was included as a potential measure of the propensity to harvest for the plot. We also included the growing stock removals in cubic feet (from FIA county data) per unit of county

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\[9\] Historically FIA provides detailed data on forest inventory for all the states on approximately 10-year periodic cycle with each plot roughly representing a 3×3 mile grid pattern

\[10\] Census collects decennial data and so for the FIA counterpart of 1972 and 1982 we used its closest census counterpart which was 1970 and 1980.

\[11\] Bureau of Census definition for a place is “concentration of population either legally bounded as an incorporated place, or identified as a Census Designated Place (CDP) including comunidades and zonas urbanas in Puerto Rico. Incorporated places have legal descriptions of borough (except in Alaska and New York), city, town (except in New England, New York, and Wisconsin), or village”.

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land area in acres (from ERS) as a proxy for forest land use return (RET) hypothesized as one of the chief economic drivers of land use change in almost all of the previous land use models. SLOPE in percent for the FIA plots was included to examine the potential influence of topography on landowner choice. Finally, to explore the full potential of the urbanization pressures acting on forest land use change, county level estimates of per capita personal income (INC) from REIS of the BEA deflated by the Consumer Price Index (Urban South, 1982=100), and county level estimates of population density (PD) were also included in the model. A list of the variables used in the analysis with their sources and standard statistical summary is given in Table 1.

### Table 1 Univariate statistics of the variables and their description

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
<th>Mean</th>
<th>Std.dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PGI</td>
<td>Number of persons/Km² around each FIA plot within 100 Km radius of each FIA plot</td>
<td>FIA plot and Census Bureau</td>
<td>136.03</td>
<td>99.60</td>
</tr>
<tr>
<td>VOL</td>
<td>Average volume in cubic feet per acre for the FIA plots</td>
<td>FIA plot data</td>
<td>1027.19</td>
<td>965.92</td>
</tr>
<tr>
<td>SW</td>
<td>Initial forest type dummy for Softwood forest</td>
<td>FIA plot data</td>
<td>0.35</td>
<td>0.47</td>
</tr>
<tr>
<td>MX</td>
<td>Initial forest type dummy for Mixed forest</td>
<td>FIA plot data</td>
<td>0.44</td>
<td>0.50</td>
</tr>
<tr>
<td>HW</td>
<td>Initial forest type dummy for Hardwood forest</td>
<td>FIA plot data</td>
<td>0.20</td>
<td>0.40</td>
</tr>
<tr>
<td>INC</td>
<td>Real (1982=100) per capita personal income by county in $</td>
<td>BEA</td>
<td>111.95</td>
<td>23.48</td>
</tr>
<tr>
<td>RET</td>
<td>Growing stock removals in cubic feet per acre of county land area</td>
<td>FIA county data and ERS</td>
<td>37.53</td>
<td>18.40</td>
</tr>
<tr>
<td>SLOPE</td>
<td>Slope in percent for FIA plot</td>
<td>FIA plot data</td>
<td>9.93</td>
<td>10.75</td>
</tr>
<tr>
<td>PD</td>
<td>Number of persons per unit of land area by county</td>
<td>Census Bureau</td>
<td>73.28</td>
<td>97.75</td>
</tr>
</tbody>
</table>

### Population Gravity Index

A 100km [12] buffer around Alabama incorporating the influence of census places from the four contiguous states of Georgia (GA), Tennessee (TN), Mississippi (MS) and

[12] 100 km within an average 60-minute commute time from FIA plots was assumed as the threshold distance and varying this distance did not substantially affect the sign and magnitude of the estimated coefficients of the gravity index and other variables.
Florida (FL) in addition to all the designated census places within the state of Alabama was created. Population Gravity index (PGI) for a plot \( k \) was specified as

\[
P_{G I k} = \frac{\sum_{p} P_{pt}^{2}}{D_{kp}^{2}} \quad \forall \; p : D_{kp} \leq 100 \, km
\]

where \( P_{pt} \) is the population of populated place \( p \) at time \( t \), and \( D_{kp} \) is the distance between FIA plot \( k \) and populated place \( p \).

PGI was previously found to be positively correlated with conversion to non-forest use from forest use (Majumdar et al. 2005).

**Results**

The three utility functions representing the variables likely to influence landowners’ decisions at the three decision nodes of the nested tree and the attribute vectors in \( y, z, \) and \( x \), are:

Pr(no harvest relative to harvest) \( \equiv f(VOL, SLOPE, SW) \) (9)

Pr(Non-forest relative to Forest) \( \equiv f(PGI, INC, RET, PD) \) (10)

Pr(Softwood or Mixed or Hardwood) \( \equiv f(SW, MX, HW, PGI) \) (11)

We estimated a three level nested logit model in which the landowner decides to either harvest or not to harvest at the top level, then makes the decision to convert the harvested plots into non-forest use or keep them in forest use at the next level, and finally decides on whether the forested plot will be of softwood, mixed hardwood, or hardwood forest type at the lowest level (see Figure 1 for the nested tree depiction).

The reference category \( [14] \) in (9) was harvest and in (10) forest. In (11) the reference category was hardwood (for PGI) and no change in forest type for the variable initial forest types (SW, HW or MX) respectively. The results are summarized in Table 2.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Odds Ratio</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Harvest Vs. Harvest</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SW × CNH</td>
<td>-0.5714</td>
<td>0.059*</td>
<td>0.56</td>
<td>-9.61</td>
</tr>
<tr>
<td>SLOPE × CNH</td>
<td>0.0217</td>
<td>0.002*</td>
<td>1.02</td>
<td>10.12</td>
</tr>
<tr>
<td>VOL × CNH</td>
<td>0.0009</td>
<td>0.00003*</td>
<td>1.00</td>
<td>32.31</td>
</tr>
<tr>
<td>Non-Forest Vs. Forest</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PGI × CNF</td>
<td>0.0011</td>
<td>0.0005**</td>
<td>1.00</td>
<td>2.16</td>
</tr>
<tr>
<td>RET × CNF</td>
<td>-0.0172</td>
<td>0.004*</td>
<td>0.98</td>
<td>-4.40</td>
</tr>
<tr>
<td>PD × CNF</td>
<td>0.0019</td>
<td>0.0005*</td>
<td>1.00</td>
<td>3.99</td>
</tr>
<tr>
<td>INC × CNF</td>
<td>-0.4266</td>
<td>0.0397*</td>
<td>0.65</td>
<td>-10.75</td>
</tr>
<tr>
<td>Forest Type</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MX × CSW</td>
<td>-1.9815</td>
<td>0.1225*</td>
<td>0.14</td>
<td>-16.17</td>
</tr>
</tbody>
</table>

[13] Kline et al (2001) used a similar formulation of gravity index but with different exponents on the population and distance components of the index and they used three cities with population greater than 5000 and greatest urban influence based on their gravity index on each FIA plot.

[14] With all the explanatory variables being characteristics of the FIA plot and not the alternative land use choices we used interactions of each variable with the dummy of choice alternatives and hence had to remove a particular choice and make it as a reference base for model identification.
<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>z-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>MX × C_HW</td>
<td>-2.3806</td>
<td>0.1032*</td>
<td>0.09</td>
<td>-23.06</td>
</tr>
<tr>
<td>HW × C_SW</td>
<td>-0.2388</td>
<td>0.1184**</td>
<td>1.49</td>
<td>4.41</td>
</tr>
<tr>
<td>HW × C_MX</td>
<td>0.4010</td>
<td>0.0909*</td>
<td>0.79</td>
<td>-2.02</td>
</tr>
<tr>
<td>SW × C_MX</td>
<td>-0.9931</td>
<td>0.0857*</td>
<td>3.7</td>
<td>-11.59</td>
</tr>
<tr>
<td>SW × C_HW</td>
<td>-1.2661</td>
<td>0.0874*</td>
<td>0.28</td>
<td>-14.48</td>
</tr>
<tr>
<td>PGI × C_SW</td>
<td>-0.0045</td>
<td>0.0005*</td>
<td>0.99</td>
<td>-8.72</td>
</tr>
<tr>
<td>PGI × C_MX</td>
<td>-0.0002</td>
<td>0.0003*</td>
<td>99.41</td>
<td>-6.88</td>
</tr>
</tbody>
</table>

| IVc (Forest) | 0.87 | 0.1360* | 6.42 |
| IVc (Harvest) | 0.85 | 0.1311* | 6.48 |
| Log likelihood | 10096 |
| McFadden’s LRI | 0.39 |
| Observations | 10383 |

<table>
<thead>
<tr>
<th>Note</th>
<th>Represent the dummies for the choice alternatives softwood, mixed, hardwood, non-forest and no harvest respectively</th>
</tr>
</thead>
<tbody>
<tr>
<td>Note</td>
<td>IV were constrained to be the same at each nest level for model identification, moreover for degenerate branches the such as Non-forest and No harvest IVs cannot be identified (for detail see Hunt 2000), * p &lt; 0.10, ** p &lt; 0.05</td>
</tr>
</tbody>
</table>

The nesting structure in figure 1, together with equations (5)-(7) and (9)-(11) can be used to formulate appropriate log likelihood function to estimate the parameters of the model. The nested logit model was estimated using full information maximum likelihood estimation in SAS 9.1. Maddala (1983, page 73) states that if the IV parameters lie outside the range of zero to one then this should be considered as evidence for a specification error and warrants re-examination of the model. Further McFadden (1981) states that if the dissimilarity coefficients (IV coefficients) are larger than 0 and not statistically larger than 1, it can be concluded that the nested model is consistent with stochastic utility maximization. The results support the choice of a nested logit model, over a more restrictive multinomial logit model that does not allow for correlation within nests. The estimated maximum likelihood nested logit model had a reasonable fit with McFadden likelihood ratio index statistic (pseudo-\( R^2 \)) being 0.39.

No Harvest Vs Harvest

SW, representing the initial forest type as pine, had the expected negative sign and indicates less likelihood of no harvest of a pine plot. In other words there is a greater likelihood that pine plot will be harvested relative to hardwood or mixed plot. SLOPE had the expected positive sign with the statistically significant parameter estimate which indicates that with an increase in slope there is a greater likelihood of no harvest due to a possible hindrance to accessibility of logging equipment and associated increase in harvesting cost. Moreover steep slope also constrains excessive harvests to prevent erosion. The result is consistent with previous studies (Wear and Flamm 1993).

VOL, denoting the average volume per acre in cubic feet for the FIA plot had a positive sign. This implies that higher the volume the less likely it will be harvested. This is contrary to our expectation that greater average volume would lead to a greater probability of harvest. A
close examination \(^{15}\) reveals that most of the harvests took place in the softwood plantation type, which typically has lower average volume in comparison to the hardwood plots.

**Non-forest Vs Forest**

The population gravity index (PGI), representing the developmental pressure on forestland, had a statistically significant positive coefficient indicating that with an increase in PGI there is a greater likelihood of forestland conversion to non-forest use. This is an expected result since in general demand for developed land near the population centers with higher PGI is high in comparison to the demand for forests. Researchers have found other measures of urbanization like increase in population density (Nagubadi and Zhang 2005) and decrease in distance from the center of the county to the nearest city (Ahn et al 2002) to favor an increasing non-forest share of land.

INC had a statistically significant negative coefficient suggesting that counties with higher real per capita income are more likely to maintain their forests, with less inclination for conversion to non-forest use, *ceteris paribus*. This is contrary to the expectation of a casual observer and inferences drawn from previous research (Zhang and Nagubadi 2005). The intuitive explanation could be that with an increase in income the landowner may perceive the returns from the consumptive use (aesthetics, amenities) of his forestland as higher in comparison to the return that can be gained with conversion to a developed use (intuitively somewhat like an environmental Kuznets curve).

RET, denoting the total amount of removals of growing stock from all the FIA plots within a county adjusted for the difference in county land area in cubic feet per acre has a negative coefficient and is statistically different from 0 at the 1% level of significance. This result is consistent with our expectation, since counties with higher timber removals represent the timber basket of the state and have less likelihood of forestland conversion to other uses. This result is consistent with the Ricardo-Thünen land rent theory of land use change that proposes that land is put to the land use alternative that provides the highest land rent. Positive forest use returns (denoted by higher RET) are expected to decrease the likelihood of forest conversion to non-forest use.

PD had a statistically significant positive coefficient reflecting the increased likelihood that a plot will be converted to non-forest use when there is an increase in demand for land for residential purposes, a result consistent with past studies on land use change (Wear et. al 1998, Nagubadi and Zhang 2005).

**Forest Types**

The negative parameter estimate for five out of the six (except HW × CM) \(^{16}\) initial forest type variables indicates less likelihood of a forest type transition from one type to another relative to its likelihood of remaining as the same type reflects the costs of conversion constraints (Alig and Butler 2004). However the positive estimate for hardwood plots to be regenerated into a mixed type (HW × CM) following harvest indicates a contrary

\(^{15}\) Separate models had to be estimated which could include interaction terms of VOL and the initial forest type keeping the VOL main effect for each forest type due to collinearity problem and results showed the coefficient of the interaction term of pine with the average volume as negative while that of the hardwood and mixed as positive

\(^{16}\) CSW, CMX, CHW, CNF, CNH refer to the choice alternatives: softwood, mixed, hardwood, non-forest and no harvest respectively.
result. Zhou et al. (2003) found a significant percentage of FIA plots in the South (upland hardwood), which were not harvested, transitioned to a mixed type in the subsequent survey and considering that there were a large percentage of plots (53.2%) in our study that were not harvested, this result seems reasonable. Also depending on the FIA classification\textsuperscript{[17]} of a forest type, it is possible that a stand classified as hardwood could be retyped as a mixed type in the subsequent census.

The negative significant parameter estimate for $PGI \times C_{SW}$ and $PGI \times C_{MX}$ reveals landowners’ (who are closer to population centers) preferences for regeneration of hardwoods.

**Discussion**

The nested logit model seems to be an appropriate choice for studying the discrete choice behavior of the private forest landowner. It is superior to multinomial logit, an econometric technique widely used to model land use, and allows for correlation of the error terms within a nest of similar choices. To our knowledge application of the nested logit technique to analyze the forest harvesting decision by the landowner has not been considered previously. Our results show that the initial forest type and population gravity index are significant variables in explaining the variation in type transition. Consistent with previous research findings population gravity index, a proxy for the anthropogenic influence, favored forest land conversion to non-forest use.

The probability that a forest plot will be converted to non-forest at the mean of all the explanatory variables in the model is 0.02. In the softwood, mixed and hardwood forest types those probabilities increased to 0.05, 0.17 and 0.06 following harvest. The probability of no harvest at the mean of the variables was 0.7. In summary, given the 21.7 million acres of private timberland (Hartsell and Brown 2000) our model projects 434,000 acres to be converted from forest to non-forest use over a period of the next 10 years. For the same period the acreage of non-harvested forest plots is projected to be 15.19 million acres with 1,085,000 acres, 3,689,000 acres and 1,302,000 acres of harvested timberland projected to be regenerated as softwood, mixed and hardwood forest types respectively. These results are consistent and can be used for short-term predictions.

\textsuperscript{[17]} A classification of forest land is commonly based upon, and named for, the tree species that forms the plurality of live-tree stocking.
References


