FAMILY FOREST LANDOWNER BEHAVIOR IN THE SOUTHEAST

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FAMILY FOREST LANDOWNER BEHAVIOR IN THE SOUTHEAST

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Indrajit Majumdar son of Mrinal Kumar Majumdar and Subha Majumdar was born in Bihar, India. After finishing high school from Delhi Public School, India he went on to complete his BS. in Botany from Delhi University in 1997 and his MS. in Forest Economics and Management from the Forest Research Institute, Dehradun, India in 2000. After a small stint of work in a project funded by the International Crops Research Institute for the Semi-arid Tropics (I.C.R.I.S.A.T.) in Hyderabad, India, during December 2000-January 2001 he joined Auburn University in the fall of 2002 for his graduate studies. He was married on 27th November, 2004 to Anindita, daughter of Deba Prasad Dutta and Atasi Dutta from Durgapur, India.

DISSERTATION ABSTRACT

FAMILY FOREST LANDOWNER BEHAVIOR IN THE SOUTHEAST

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Forests and forestry have played a significant role in the economic development and psyche of the South. Forests, which pre-settlement occupied nearly all of the land area of the South, now occupy only 55 percent. More important, perhaps, is the change in the structure and composition of these forests. Some of these changes have resulted from harvest for conversion to agriculture, and the subsequent reversion to forest. Other changes have occurred as fiber demand increased and harvested lands were replanted with pines. More recent is the recognition that forests provide amenity and recreational values which may lead to reductions in harvest by family forest owners. With an unprecedented growth in the number of family forest landowners there is an increase in the surge for researchers to investigate the motives of these landowners to manage their land for timber and/or non-timber use. The diversity amongst these owners in terms of

their objectives and their forest conditions coupled with the increasing urbanization pressure warrants need for a thorough investigation. This study presents result from investigating the complexities of family forest owner behavior in three separate chapters (2, 3 & 4) which can be read independently and is styled in journal publication format.

Chapter 2 explores the impacts of population pressures on forestland use change in Alabama and results suggest initial forest type and population gravity index to be significant correlates to forest type transition and conversion o forest to non-forest use. Measures of anthropogenic influence such as population density and real per capita income had significant impact on conversion of forest to non-forest use. We also found that Nested Logit is a appropriate econometric technique to study the discrete choice behavior of private landowners.

Chapter 3 investigates the diversity of motivations of family forest owners in the Southeast and tests the assumption of homogeneity (treating family forest owners as a single homogeneous group) that previous researchers have made. Our study using multivariate cluster analysis procedures suggest that family forest owner 'group' is in fact a diverse set of owners who can be grouped into three attitudinal types namely *multiple-objective*, *non-timber* and *timber*.

Finally, in Chapter 4 multivariate non-parametric discriminant procedures was used to discriminate the three attitudinal groups (Chapter 3) using bio-physical, socio-economic and demographic variables. Analysis results indicate that 84% of landowners across all landowner groups were correctly classified. With all the variables used to develop the classification scheme in this study known, *a-priori*, that is before landowners on a Forest Inventory and Analysis (FIA) plot location is contacted for the National Woodland Owner Survey (NWOS), it may be possible to predict membership of a future landowner with known FIA and Census demographic attributes.

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CHAPTER 1

INTRODUCTION

Forest ownership patterns are rapidly changing due to broad-based sale of forest land by the major forest product firms and the subsequent parcelization of those lands into smaller ownerships through successive rounds of purchase and resale by intermediate land brokers. At the same time family forest management in the Southeast is undergoing significant change due to the evolving motivations and values of new family forest owners, their reduced reliance on land-based occupational income, and general urbanization pressures on land use decisions. The economic and societal impacts of these changes still remain largely unknown.

Substantial research has been conducted over the last few decades regarding the factors influencing the behavior of private forest owners with the underlying goal to identify more effective ways of communicating/encouraging family forestland owners to actively practice forest management. The non-consumptive uses of family forests and the psychic tradeoffs between the timber production (primarily for profit) and the non-timber (amenities) consumption (primarily for utility) for the family forest owners have often been neglected. Identifying these diverse motivations and the subjective preferences for managing their forest for timber and/or non-timber amenity values is warranted in the wake of their increasing numbers.

To address the general questions stated above this study was conducted and the results are presented in three chapters (2, 3 & 4). Chapter 2 investigates the effect of increasing urbanization pressures on choices made by private landowners in Alabama. Nested logit analysis was conducted to model the land use decision making behavior of private landowners. Private landowners are assumed to choose from amongst a discrete set of management alternatives the one that maximizes their 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) and a no harvest decision maintaining initial forest type. 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. To our knowledge application of the nested logit technique to analyze the forest harvesting decision by the landowner has not been considered previously.

The names used to describe the family forest owners have changed over time, but the inclination to treat/analyze them as a homogeneous one has been fairly common. Chapter 3 characterizes the family forest owners in the three Southeastern states of Alabama, Georgia and South Carolina based on their feelings about forest stewardship and their stated reasons for owning forestland. Multivariate clustering technique was used to analyze the National Woodland Owner survey (NWOS) data on the family forest owners and results reveal the presence of three owner clusters (classes) based on their stated motivations for owning their forestland. These three owner classes were termed as *multiple-objective*, *non-timber* and *timber* respectively. The *multiple-objective* ownership type was found to be the largest group (533 owners, 49.1%) with almost every 1 out of 2 family forest owners in the sample population belonging to this category. Owners belonging to the *timber* (319 owners, 29.4%) cluster had only the timber management and land investment as the strong motivating factors behind their forestland ownership while owners belonging to the *non-timber* (233 owners, 21.5%) cluster value the non-consumptive uses of their forestland such as aesthetic values, biodiversity, recreation and privacy.

After exploring the diverse motivations and classifying the family forest owners into three groups (Chapter 3) the question of interest next was whether we could identify certain characteristics that would discriminate the landowner groups and develop a classification scheme that will help in predicting the most likely group that a new landowner will be characterized into given these characteristics. Chapter 4 presents results of this investigation. Multivariate non-parametric discriminant analysis using *k*-nearest neighbor (KNN) method was used in the study. It was found that bio-physical (Slope, Site productivity index, Forest type and Stand age), socio-economic (Median household income and Distance to nearest paved road) and demographic (Population gravity index and Population density) variables had a strong association with landowner group profiles. The average accuracy of prediction across all the landowner groups was 84% and it was 87%, 78% and 82% for *multiple-objective*, *non-timber* and *timber* owners respectively. This study indicates that landowners clustered into heterogeneous attitudinal groups (multiple-objective, non-timber and timber) can be accurately separated using non-parametric KNN technique.

CHAPTER 2

EFFECT OF URBANIZATION ON FOREST LAND USE CHANGE IN ALABAMA: A NESTED LOGIT APPROACH

2.1 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.

Prompted by the re-allocation of scarce resources to satisfy growing human needs, land use change impacts numerous ecosystem services and functions such as watershed protection, biogeochemical cycling, soil degradation, and habitats for different species.

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.

2.2 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 et al., 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. Another distinction worth mentioning between the aggregate area-based approach and the spatially explicit approach is that, in the former approach, the coefficients of the model capture simultaneously both the spatial and temporal effects of the explanatory variables and though this methodology has helped a lot in identifying the factors affecting allocation of land to different uses, it generally has done a poor job in identifying the temporal component, or the effects of factors on land use change, as well as 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.

Econometric studies on shares of land uses and forest types (Nagubadi and Zhang 2005) and shares of forest type by ownership category (Ahn et.al. 2001; Nagubadi and Zhang 2005) have been done using the aggregate approach at the county level. In the absence of a spatially explicit model, the full power of human impact is hard to explore. Some of the spatially explicit studies on the impact of development on forest land use change have been done (Munn et al. 2002; Kline et al. 2003) but they have assumed similar impact on different forest types. We wish to fill this gap by developing a spatial explicit model to investigate the impact of population pressures on changes in forest land use for different initial forest types viz. softwood, mixed hardwood and hardwood.

2.3 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 as it relaxes the assumption of Independent and Irrelevant Alternatives (IIA)[1] to account for the possible substitution patterns amongst alternative choices.

Lubowski (2002) in his study on the determinants of land use change at the national level used a nested logit framework to consider the substitution patterns amongst land use alternatives, but the scope of the study did not take into account the substitution possibility amongst different forest types. Moreover he was interested in evaluating the effect of the economic and policy factors on land use change, not the effect of population pressure as is central to this study.

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) and a no harvest[2] decision maintaining 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, $\mathbf{x}$, typically consists of data on land quality, socio-demographic, socio-economic and rent

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[1] 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.

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

(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*.[3] Assume that the landowner's utility function for choice *j* is given by:

$$V(\boldsymbol{\beta}_j, \mathbf{x}) = v(\boldsymbol{\beta}_j, \mathbf{x}) + \varepsilon_j \tag{1}$$

where $\mathbf{x}$ is the vector of attributes of plot characteristics and $\boldsymbol{\beta}_j$ is a vector of preference parameters on the observable portion of the landowner's utility function for the alternative *j*, $v(\boldsymbol{\beta}_j, \mathbf{x})$. Finally, ε_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:

$$V(\boldsymbol{\beta}_j, \mathbf{x}) > V(\boldsymbol{\beta}_k, \mathbf{x}) \quad \forall \quad j \in J, \quad k \in J, \quad k \neq j \tag{2}$$

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 $\boldsymbol{\beta}$. The structure of the model will depend heavily on the assumptions about the form of the distribution of error terms. Assuming error terms ε_j are i.i.d. with Type I Generalized Extreme Value distribution (GEV)[4], (1) and (2) could be expressed as a multinomial logit model:

$$\text{Prob}(k) = \frac{\exp(\boldsymbol{\beta}_k{}'\mathbf{x})}{\sum_{j \in J} \exp(\boldsymbol{\beta}_j{}'\mathbf{x})} \tag{3}$$

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[3] For notational simplicity the subscripts *i* and *t* will be dropped from the equations.
[4] 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).

In order that this model be estimable, one of the $\boldsymbol{\beta}_j$ needs to be set to $\mathbf{0}$. A well-known restriction associated with the model given in (3) is the Independence of Irrelevant Alternatives (IIA) due to the fact that

$$\frac{\text{Prob}(k)}{\text{Prob}(j)} = \frac{\exp(\boldsymbol{\beta}_k\,'\mathbf{x})}{\exp(\boldsymbol{\beta}_j\,'\mathbf{x})} \tag{4}$$

denoting that the ratio of probabilities of choices *k* and *j* would remain unchanged with a change in the parameters of choices other than *j* and *k*. 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 using a nested logit model supports the need for exploring alternative nesting structures in land use studies by taking into consideration the similarities between forest types.

To relax the IIA assumption in our analysis of the human impact on changes in forest land use we adopt a nested logit model, which groups similar alternatives into groups called nests thus allowing different variances for choices in different nests and correlation between choices within a nest. We use a three level nested logit model, which assumes that decisions are made at three hierarchical levels (Figure 2.1).

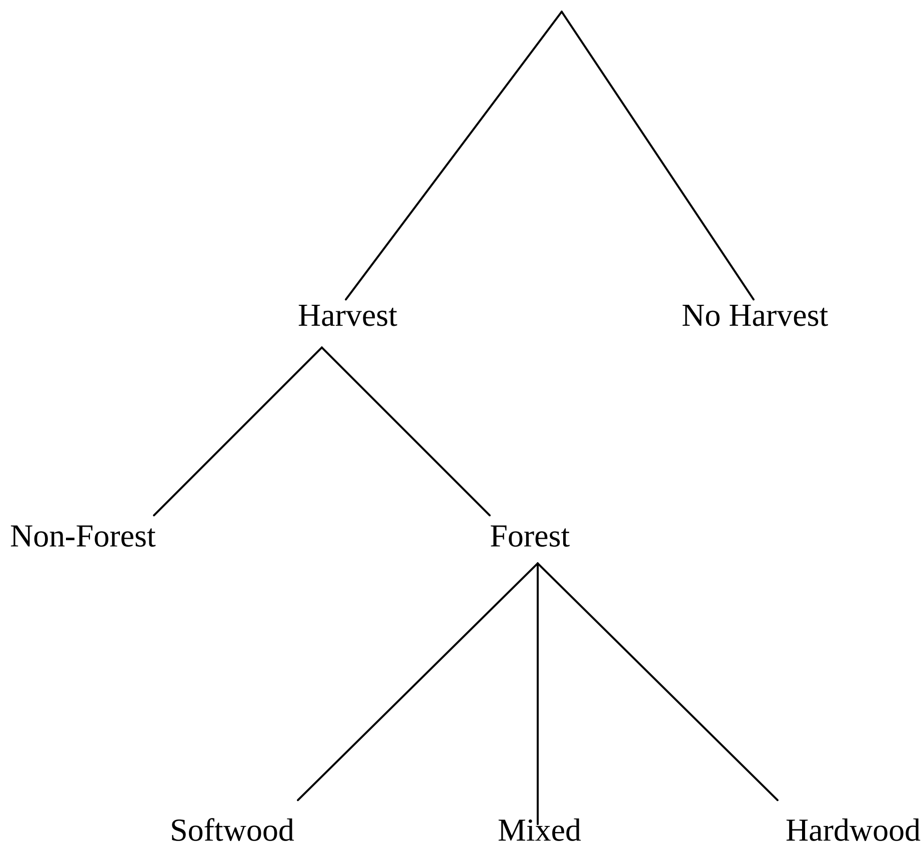

Figure 2.1 Three level-nested representation of landowner decision

The decision at each of these three levels is modeled as an outcome of separate utility functions. In other words, the landowner is seen as making an independent decision at each decision node. 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 $J = 1 \ldots J_{l,s}$ 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 $P_{ij|l,s}$ 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:

$$P_{islj} = P_{is} \times P_{il|s} \times P_{ij|l,s} = \frac{\exp(\boldsymbol{\delta}_s\,'\mathbf{y}_i + \tau_s I_{is})}{\sum_{k\in S}\exp(\boldsymbol{\delta}_k\,'\mathbf{y}_i + \tau_k I_{ik})} \times \frac{\exp(\boldsymbol{\gamma}_l\,'\mathbf{z}_i + \sigma_{l|s} I_{il})}{\sum_{m\in L}\exp(\boldsymbol{\gamma}_m\,'\mathbf{z}_i + \sigma_{m|s} I_{im})} \times \frac{\exp(\boldsymbol{\beta}_j\,'\mathbf{x}_i)}{\sum_{n\in J}\exp(\boldsymbol{\beta}_n\,'\mathbf{x}_i)} \quad (5)$$

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

$$I_{is} = \ln \sum_{m\in L} \exp(\boldsymbol{\gamma}_m\,'\mathbf{z}_i + \sigma_{m|s} I_{im}) \quad (6)$$

and

$$I_{il} = \ln \sum_{n\in J} \exp(\boldsymbol{\beta}_n\,'\mathbf{x}_i) \quad (7)$$

where, $\mathbf{y}_i$ are the observed plot attributes influencing the choice of the nest, $\mathbf{z}_i$ are the observed plot attributes influencing the choice of the sub-nest and $\mathbf{x}_i$ being the observed plot attributes influencing the decision to keep 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 $\boldsymbol{\delta}_k$ and $\boldsymbol{\gamma}_m$ are zero and the inclusive value parameters τ_k, $\sigma_{m|s}$ are jointly equal to one then the model will collapse into a multinomial logit model shown in (3).

2.4 Data and Variables

The data for this study comes from the Forest Inventory and Analysis (FIA)[5] 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[6]. 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 publicly owned plots were not considered for the study as they

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[5] 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
[6] 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.

are more predictable in terms of land use change since public land use decisions are determined mainly by forces other than the market. The total number of observations for the period (1972-2000) of the study that consisted of three transition periods was 10383. The matrix of plots by starting and end use is given in Table 2.1 for each of the three periods 1972-1982, 1982-1990 and 1990-2000. The FIA data for Alabama show a conversion of 94, 74 and 128 plots to non-forest use for the period 1972-1982, 1982-1990 and 1990-2000 respectively (Table 2.1).

Table 2.1 Matrix of number of FIA[a] plots in observed starting use and end use by period

		Ending Land Use		
Initial Land Use	Non-forest	Softwood	Mixed	Hardwood
		1972 - 1982		
Softwood	29	561	153	129
Mixed	23	142	194	185
Hardwood	42	38	102	723
		1982 - 1990		
Softwood	25	739	199	123
Mixed	17	179	282	185
Hardwood	32	104	182	1161
		1990 - 2000		
Softwood	38	843	275	305
Mixed	24	334	259	403
Hardwood	66	277	241	1499

[a] excludes all plots under public ownership and contains only privately owned FIA plots

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 a 100km. The geographic location of census places[7] 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 denoted by VOL was included as a potential measure of the propensity of harvest for the plot. We also included the growing stock removals in cubic feet (from FIA county data) per unit of county 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

[7] 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".

included in the model. A list of the variables used in the analysis with their sources and standard statistical summary is given in Table 2.2.

Table 2.2 Univariate statistics of the variables and their description

Variable	Definition	Source	Mean	Std.dev.
PGI	Number of persons/Km^2 around each FIA plot within 100 Km radius of each FIA plot	FIA plot and Census Bureau	136.03	99.60
VOL	volume in cubic feet of the FIA plots	FIA plot data	1027.19	965.92
SW	initial forest type dummy for Softwood forest	FIA plot data	0.35	0.47
MX	initial forest type dummy for Mixed forest	FIA plot data	0.44	0.50
HW	initial forest type dummy for Hardwood forest	FIA plot data	0.20	0.40
INC	Real (1982=100) per capita personal income by county in $	BEA	111.95	23.48
RET	growing stock removals in cubic feet per acre of county land area	FIA county data and ERS	20.40	12.43
SLOPE	slope in percent for FIA plot	FIA plot data	9.93	10.75
PD	number of persons per unit of land area by county	Census Bureau	73.28	97.75

2.5 Population Gravity Index

Gravity models were initially developed by Reilly (1929) to describe the degree to which cities attracted retail trade from surrounding locations. In this study a population gravity index was created to explore the combined effects of population and proximity to city centers. A 100km[8] buffer around Alabama incorporating the influence of Census places from the four contiguous states of Georgia (GA), Tennessee (TN), Mississippi (MS) and Florida (FL) in addition to all the designated census places within the state of Alabama was created. Population Gravity index (PGI)[9] for a plot *k* was specified as

$$PGI_k = \sum_p \frac{P_{pt}}{D_{kp}{}^2} \quad \forall\ p : D_{kp} < 100\ km \tag{8}$$

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*.

Location coordinates for measuring the Euclidian distance in (8) was computed using ArcGis 9.0. The gravity index itself using the population of the census place around FIA plots and distance of the FIA sample plots to census places was calculated in SAS 9.1. PGI was previously found to be positively correlated with conversion to non-forest use from forest use (Majumdar et al. 2005).

2.6 Results

Acknowledging the fact that different factors may be important at different nesting levels, we define below 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 $\mathbf{y}_i$, $\mathbf{z}_i$ and $\mathbf{x}_i$ above as

$$\text{Pr(no harvest relative to harvest)} \equiv f(VOL, SLOPE, SW) \tag{9}$$

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[8] 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.
[9] 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.

$$\Pr(\text{Non-forest relative to Forest}) \equiv f(PGI, INC, RET, PD) \tag{10}$$

$$\Pr(\text{Softwood or Mixed or Hardwood}) \equiv f(SW, MX, HW, PGI) \tag{11}$$

The reference category[10] 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 2.3.

[10] 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 2.3 Nested Logit Parameter estimates for the three-level nested model

Variable	Coefficient	Standard Error	Odds Ratio	t-statistic
		No Harvest Vs. Harvest		
SW × C_{NH}	–0.5714	0.059*	0.56	–9.61
SLOPE × C_{NH}	0.0217	0.002*	1.02	10.12
VOL × C_{NH}	0.0009	0.00003*	1.00	32.31
		Non-Forest Vs. Forest		
PGI × C_{NF}	0.0011	0.0005**	1.00	2.16
RET × C_{NF}	–0.0172	0.004*	0.98	–4.40
PD × C_{NF}	0.0019	0.0005*	1.00	3.99
INC × C_{NF}	–0.4266	0.0397*	0.65	–10.75
		Forest Type		
MX × C_{SW}	–1.9815	0.1225*	0.14	–16.17
MX × C_{HW}	–2.3806	0.1032*	0.09	–23.06
HW × C_{SW}	–0.2388	0.1184**	0.79	–2.02
HW × C_{MX}	0.4010	0.0909*	1.49	4.41
SW × C_{MX}	–0.9931	0.0857*	0.37	–11.59
SW × C_{HW}	–1.2661	0.0874*	0.28	–14.48
PGI × C_{SW}	–0.0045	0.0005*	0.99	–8.72
PGI × C_{MX}	–0.002	0.0003*	0.99	–6.88
IV[e] (Forest)	0.87	0.1360*		6.42
IV[e] (Harvest)	0.85	0.1311*		6.48
Log likelihood	10096			
McFadden's LRI	0.39			
Observations	10383			

[a] C_{SW}, C_{MX}, C_{HW}, C_{NF}, C_{NH} represent the dummies for the choice alternatives softwood, mixed, hardwood, non-forest and no harvest respectively

[e] 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)

* $p < 0.10$

** $p < 0.05$

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 2.1 for the nested tree depiction).

Land use choices are influenced at least in part by the environment of the landowner and with the increasing population and expanding metropolitan areas landowners are subjected to increasing anthropogenic pressures that influence decisions about their land use. We also think that depending on the initial use of the land this factor acts differently both in magnitude and in direction such that it has differential impacts on the decision of the landowner.

The focal point of the research was to explicitly define the decision environment of the landowner using the location of their forest plot in relation to the location of the population center and the mass of the population and then analyze their effects on the landowner decision.

The nesting structure in figure 2.1, together with equations (5)-(7) and (9)-(11) can be used to formulate appropriate log likelihood function to estimate the parameters of the model. Nested logit model was estimated using full information maximum likelihood estimation in SAS 9.1. Because one of the nests at each level contains only one alternative, this model is partially degenerate, and therefore over parameterized with respect to the inclusive value (IV) parameters (Hunt, 2000). According to Hunt (2000) "In general, the degenerate partition's IV parameter can be restricted to any value and the estimates obtained for the model will be invariant". Therefore, in order to estimate the model, we constrained IV parameters at each nest level to be equal. The hypothesis that the coefficients of the IV parameters are simultaneously equal to 1 was rejected at more than the 99% level of significance based on the likelihood ratio test confirming the validity of the proposed econometric framework. 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. A major test of the correct specification of the nested model is that the IV parameters should lie within the range of zero to one. 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 estimated maximum likelihood nested logit model had a reasonable fit with McFadden likelihood ratio index statistic (pseudo-R^2) being 0.39. There are several methods of interpreting estimates of probability models (Long 1997) but one of the easiest ways is that of the odds ratio (Liao 1994) which is the exponentiated logit coefficients estimated in the model (Table 2.3). Odds ratio values greater than 1 indicate that an increase in the independent variable translates into greater probability of that category relative to the base (reference) category, values less than 1 indicate a decrease in probability with an increasing independent variable and values at 1 indicate equal probability of the particular category and the base. For example, increases in the INC significantly decreased the conversion probability of forest to non-forest use relative to a reference category of stable forest practice with no change in land use. We employ the interpretation of the parameter estimates at each of the three decision nodes (in separate sections) of the landowner decision hierarchy (refer to Figure 2.1) by using the odds ratio in the following discussion.

2.6.1 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. The odds of a pine plot not to be harvested, *ceteris paribus*, is 0.56. In other words there is a greater probability of a harvested plot to be a pine plot relative to its being either a hardwood or a 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 and increase in cost of maintaining land in productive use. The result is consistent with previous studies (Wear and Flamm 1993). The odds that the plot will not be harvested relative to it's being harvested owing to a unit increase in slope is 1.02.

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[11] 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.

[11] 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

2.6.2 Non-forest Vs Forest

The population gravity index (PGI), representing the developmental pressure on forestland, had a statistically significant positive coefficient indicating an increase in 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 a 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). Our results show though that for a one unit increase in county real per capita income, the odds that forest will be converted to non-forest use is 0.65. 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 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 the1% level of significance. This result is consistent with our expectation, since with an increase in growing stock the potential of future returns to forest use are higher and so less conversion to non-forest occurs. The decrease in odds in favor of conversion from forest to non-forest use due to an increase in a unit of RET, *ceteris paribus*, is 0.98. This result is consistent with the landuse change based on the Ricardo-Thünnen land rent theory. 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).

2.6.3 Forest Types

The negative parameter estimate for five out of the six (except HW × C_{MX})[12] 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. The decrease in odds of a mixed type of forest transition to softwood (MX × C_{SW}) or hardwood (MX × C_{HW}) relative to its regeneration as the same mixed type are 0.14 and 0.09 respectively. The log odds of the HW × C_{SW} transition has a negative sign denoting that a hardwood plot has less likelihood of being converted into softwood relative to its remaining in the same type, with the odds being 0.79. On the other hand the increase in the odds that hardwood plots will be regenerated into a mixed type (HW × C_{MX}) following harvest is 1.49. This result is somewhat contrary to what might be expected, although Zhou et al.

[12] C_{SW}, C_{MX}, C_{HW}, C_{NF}, C_{NH} refer to the choice alternatives: softwood, mixed, hardwood, non-forest and no harvest respectively.

(2003) found a significant percentage of FIA plots in the South (Upland hardwood), which were not harvested, that 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[13] 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 decrease in odds of softwood (pine) plot to be regenerated as a mixed (SW × C_{MX}) or hardwood (SW × C_{HW}) following harvest relative to its remaining in the same type are 0.37 and 0.28 respectively.

Results on forest type transition are consistent with our *a priori* anticipation that the landowner will most likely maintain the same forest type due to the costs of conversion, a result consistent with previous studies by Zhou et.al. (2003) and Alig and Butler (2004). Zhou et.al. (2003) projected that most of the hardwood and mixed oak-pine stands will remain as the same type in future surveys following harvest. Similarly Alig and Butler (2004) found that the forest types having the highest probability of remaining as the same type in subsequent forest inventories following partial and final harvest are the lowland hardwood and the oak-pine.

The negative significant parameter estimate for PGI × C_{SW} and PGI × C_{MX} reveals landowners' (who are closer to population centers) preferences for regeneration of hardwoods. The decrease in odds of a forest plot to be regenerated as softwood or mixed type relative to hardwood due to an unit increase in PGI, *ceteris paribus*, is 0.99. This indicates that hardwoods with their higher non-timber amenity values may be preferred,

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[13] A classification of forest land is commonly based upon, and named for, the tree species that forms the plurality of live-tree stocking.

albeit marginally, by landowners near urbanized centers relative to other forest types with relatively low aesthetic values.

2.7 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 timberland projected to be regenerated following harvest as softwood, mixed and hardwood forest types respectively. These results are consistent and can be used for short-term predictions.

2.8 Conclusion

We used a discrete choice random utility model to investigate landowner choices among a discrete number of land use alternatives using a nested logit model. We took into consideration the characteristics of the decision environment of the landowner, considering primarily the forest's location relative to urban influences and certain forest characteristics. This paper illustrates the importance of considering possible correlations between similar alternative choices in modeling landowner decisions.

In the model we assume that the utility functions for all the private landowners have the same correlations amongst the functions' random components for all the choice alternatives. In reality these correlations might vary widely among decision makers Future studies can explore these differences by analyzing the data separately for private ownership categories like non-industrial private owners and industrial owners. We do not make adjustments for the potential spatial correlation of the model error terms and assume that the systematic sampling of plots (roughly on a 3-mile grid with each plot approximately representing 6000 acres) minimizes the likelihood that plots fall under the same ownership.

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CHAPTER 3

FAMILY FOREST OWNERS IN THE SOUTHEAST: ARE THEY ALL THE SAME?

3.1 Introduction

Forests and forestry have played a significant role in the economic development and psyche of the South. Forests, which in pre-settlement times occupied nearly all of the land area of the South, now occupy only 56 percent ((Economic Research Services of the USDA 2002)http://www.ers.usda.gov/Data/MajorLandUses/MLUsummarytables.pdf). More important, perhaps, is the change in the composition and use of these forests. Some of these changes have resulted from forest conversions to agriculture, and subsequent reversions back to forest (Healy 1985). Other changes occurred as fiber demand increased over time and harvested lands were replanted with pines. More recent is the recognition that forests provide significant amenity and recreational values, which may lead to reductions in harvest by non-industrial private forest landowners.

While forests provide both market and amenity outputs, these outputs are not necessarily complementary. The dominant market output is timber, the harvest of which often conflicts with production of high-quality amenity benefits. Thus, the values held by private landowners for amenities play a role in influencing private forest management by changing the harvest date or amount of timber produced from any given stand.

With the unprecedented recent growth in the number of private forest landowners there is an increased need to research and investigate the motives of these landowners to manage their land for timber and/or non-timber use. Three broad categories of ownership constitute what we consider private forestlands: family owned or individual owners, industrial ownership, and Timber Investment Management Organizations (TIMOs) or Real Estate Investment Trusts (REITs). While of these latter two are considered to be primarily in the business of forestland management for profit and invariably their management actions focus on timber harvests, the objectives of the former, individual forestland owners, still remain largely unknown. The individual and family forest landowners hold 42% of the nations timberland ((261.6 million acres) and 59% (127.6 million acres) in the South (Butler and Leatherberry, 2004). Given their numbers it is important to study their diverse objectives, goals and intentions for managing their lands for timber and/or non-timber purposes.

Substantial research has been done over the past few decades focusing mainly on ways to motivate the family forest landowners to practice active forest management to boost timber supply. The relationship between harvesting decisions and the characteristics of landowners (Binkley 1981) has been the focus of most studies on private forest management behavior. The relationship between forest amenity characteristics and private forest harvest, however, has not been well established. One feature of all of the studies, with some exceptions (Butler 2005; Kluender and Walkingstick 2000; Finley 2002; Green and Blatner 1986; Gramann et al. 1985; Young and Reichenbach 1987) is to consider individual private landowners as a homogeneous, single group with similar motivations. In reality, the validity of this assumption is questionable.

This article tests the hypothesis that family forest landowners form a heterogeneous group with differing motivations and goals for forest management, and that even when they face the same market environment their actions differ.

3.2 Literature Review

The two most widely researched aspects of NIPF behavior, which have been at the center of studies over the past few decades, are their harvest (Binkley 1981, Boyd 1984, Dennis 1990, Hyberg and Holthausen 1989, Pattanayak et al. 2003) and reforestation behavior (Alig 1986, Newman and Wear 1993, Kline et al. 2002)[14]. Family forest owners[15] are often considered as a single entity, while their increasing numbers and ownership statistics suggest that they are a heterogeneous group with diverse objectives for managing their land. Almost 4 out of 7 family forest owners in the South owns less than 10 acres of land and constitute 5.6% of all family forests in the South. Very few studies in the US on NIPF behavior in general have explicitly considered categorizing forest owners according to their diversity in attitudes, objectives and non-timber values.

Using data from a survey of 146 Finnish landowners in Southern Finland, Kuuluvainen (1996) employed K-means cluster analysis to empirically identify four groups of non-industrial private forest landowners (NIPFs) owners based on their objectives as *multiobjective owners*, *self-employed owners*, *recreationists* and *investors*. Lewis (1979) and Kurtz and Lewis (1981) utilized Q-methodology to construct a

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[14] For an excellent review of literature on NIPF studies see Beach et al. 2005.

[15] Family forest owners are defined as ‘family forests include lands that are at least 1acre in size, 10% stocked, and owned by individuals, married couples, family estates and trusts, or other groups of individuals who are not incorporated or otherwise associated as a legal entity’ (Butler and Leatherberry 2004)

taxonomy of family forest owners in the USDA Forest Service Eastern Ozarks region of Missouri and identified four attitudinal types which were identified and described as *timber Agriculturists*, *timber conservationists*, *forest environmentalists* and *range pragmatists*.

More recently, a survey of 866 family forest owners in Arkansas and subsequent cluster analysis identified four distinct groups of family forest owners: *timber managers, resident conservationists*, *affluent weekenders* and *poor rural residents* (Kluender and Walkingstick 2000). The types described by Kluender and Walkingstick (2000) were constructed using a combination of demographic and management characteristics. Using objective demographic characteristics of the landowners as variables to classify them fail to take into account explicitly the subjective attitudinal or psychic constructs of landowner motivations, which can be considered as latent qualities of the landowner. While forest management actions may differ from landowners' philosophies about forestland stewardship based on certain external factors, it is expected that their perceptions and motivations determine the nature of their forest management activities in the long run.

Kittredge (2004) suggests that market segmentation may provide a superior approach to outreach compared with the traditional methods that assumed a single more homogeneous group of family forest owners. Market segmentation allows the audience to be broken down into relatively homogeneous similar classes, and the needs and desires of each class can then be ascertained. With the ownership class identified, certain groups can be chosen as priority targets for specific outreach programs. For example, Broderick et al. (1996) grouped family forest owners in Connecticut based on their intentions concerning forest stewardship planning. The groups consisted of those who intended to sell their land (*sellers*), those who had a stewardship plan or had protected their land (*planners*), those who intended to develop a stewardship plan (*intenders*), and those who showed little inclination towards stewardship planning (*non-intenders*).

Kendra and Hull (2005) used cluster analysis to group family forest owners who had recently purchased forestland in rapidly growing counties in Virginia. In this case, the typology was based solely on the owners' responses to survey items measuring forest ownership motivations. The resulting six types were then described on the basis of demographic, land ownership and management characteristics and labeled *absentee investors*, *professionals*, *preservationists*, *young families*, *forest planners*, and *farmers*. This study serves as a very recent example of a typology of family forest owners for which the classification was based on purely psychological variables. Though this study is significant in exploring the motivations of new owners and their reasons for acquiring forestland it fails to validate the results due to the absence of data on any of the past actions of the owners and as such the connection between landowner attitudes and their probable management actions in the future could not be made.

Various studies have been done on family forest owner attitudes in the South. Although these have not explicitly considered grouping landowners into homogeneous attitudinal groups, they do give some insight to perceptions of an average forest owner. Bliss and McNabb (1992) found that 43 percent of Alabama family forest owners believed that forestry should be regulated on private lands to protect the environment.

Contrary to this result a recent study by Kennedy and Roche (2003) revealed that 55 percent of Alabama family forest owners believed, 'Providing timber and wood products' was the most important role of their forests. Birch (1997) found that in Alabama 27 percent of landowners felt that 'residence' was the primary objective of land ownership and 56 percent reported to having done timber harvests in the past.

In a study on the NIPFs of Florida, Jacobson (1998) found 64% of landowners to be 'absentee owners' not living on their forestland and concluded that such owners are more likely to hold land for aesthetic beauty, wildlife habitat and recreation rather than timber. Newman et al (1996) reached a similar conclusion from a mail survey of the NIPFs of Georgia. Lorenzo and Beard (1996) found a significantly high correlation between the participation of NIPFs in governmental assistance programs and acreage of ownership in Louisiana.

Summarizing this section on the review of past studies, specifically those on family forest owners in the South, we see a lot of variation regarding their motivations and the management strategies they employ. Emphasizing the diversity of family forest owners in the South, Wicker (2002) stated, "available research information is insufficient to define an average private southern forest landowner."

3.3 Landowner Model

A typical rational forest landowner is assumed to maximize his utility from his forest holding by equating his preferences for timber and non-timber values to the total capacity of the land to provide these two benefits given resource and budget constraints. Based on Vincent and Binkley's (1993) model for a single stand, the optimal point where the landowner will maximize his utility depends on the interplay of the production trade-offs (the combinations of timber and non-timber units that the stand can produce) and the consumption (psychic) trade-offs which are determined by the landowners' perception of the relative value of timber and non-timber products of the forest. Binkley argues that for a single stand, unless the relative price line is either 'too' steep or 'too' flat, the multiple use option is always superior and rejects the possibility of a corner solution where the landowner chooses either to produce *only* timber or *only* non-timber. We support Vincent's and Binkley's argument that the most plausible option for family forest landowners in general is to practice multiple-use forest management in absolute terms. We argue, however, that based on the psychic price (value) that individual landowners' perceive from non-timber benefits, which typically do not have any market price, the slope of the relative price (value) line can differ to such a degree that it may be possible to group/classify landowners' based on their motivation to manage for either *only* timber or *only* non-timber or both.

To illustrate our point consider three family forest landowners' A, B and C who own single forest stands where each stand can produce two products, timber (T) and Non-timber (NT). We assume a strictly concave production possibilities frontier (PPF) for each of the three landowners consistent with the usual microeconomic assumption of increasing opportunity costs as one produces more units of a product (see Figure 3.1). The landowners maximize their utility at the tangential point between the PPF and the relative price (value) line such that landowner A produces A_T and A_{NT}, landowner B produces B_T and B_{NT} and Landowner C produces C_T and C_{NT} quantities of timber and non-timber (Figure 3.1). The object of this paper is to test the validity of the existence of similar family forest landowner groups in the Southeast as represented by landowners A, B or C using multivariate statistical techniques.

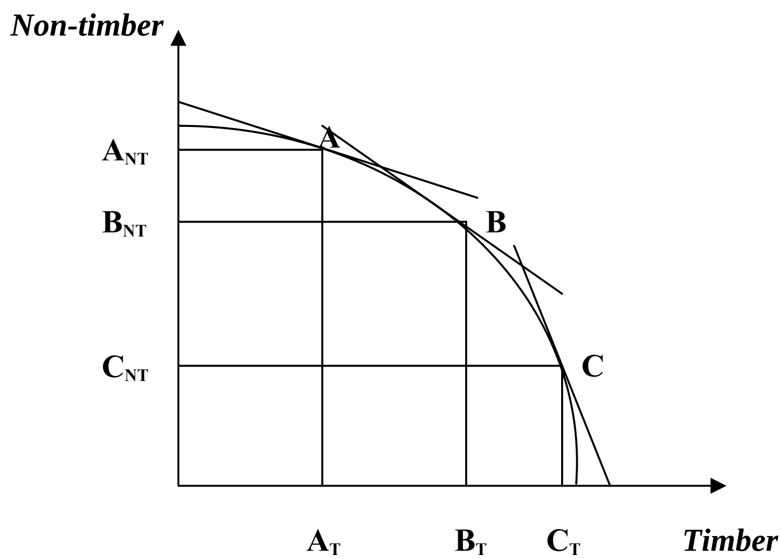

Figure 3.1 Landowner Behavior Model

3.4 Data and Methods

This study is based on the analysis of National Woodland Owner Survey (NWOS) data on the family forest owners in three Southern states: South Carolina, Georgia and Alabama. NWOS is conducted under the Forest Inventory and Analysis (FIA) program of the United States Department of Agriculture (USDA) Forest Service (USFS). The data used in this study was collected during the period 2002-2004.

The NWOS used a self-administered questionnaire distributed to family forest owners by the U.S. Postal Service as the primary survey instrument with telephone interviews conducted sometimes to augment response rates (Butler et al 2005). The questionnaire included 30 questions concerning:

- Forest land characteristics
- Ownership objectives
- Forest use
- Forest management
- Sources of information
- Concerns and issues
- Demographics

The questions in the survey were prepared using a comprehensive questionnaire review process which included expert reviews, pretesting of the survey instrument at several forest land-owner conferences and professional meetings, input from state forestry agencies, expert opinion and review by the clearance office of the USDA forest service[16].

3.4.1 Data

The total number of private landowners responding to the NWOS during the survey period in South Carolina (SC), Georgia (GA) and Alabama (AL) was 1854 (SC=753, GA=813 and AL=290). Out of these private owner responses, we discarded forest industry (FI) + TIMOs + REITs since we were interested in exploring the diverse set of motivations of the family forest owners. We assumed that the motivations of FIs, TIMOs and REITs were to generate profit from timber management. We also excluded all owners with parcel sizes less than 25 acres due to the economic inefficiencies

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[16] For a detailed description of the development and implementation of the survey instrument (NWOS) read 'Design, Implementation, and Analysis Methods for the National Woodland Owner Survey' (Butler et al 2005).

associated with managing such smaller parcels for timber, and assumed that a rational owner with the aim of maximizing his utility from the forestland had to be motivated mainly by the non-timber amenity values of the forest for a parcel smaller than 25 acres. This resulted in reducing the number of respondents included in the analysis to 1339 from 1854.

3.4.2 Statistical Methods

This study is related to the identification of family forest landowner groups based on their similar motivations to manage their land and the attached values and interests of these owners in their forestland. The questions in Table 3.1 (question number 9 in NWOS) form the basis for identifying the landowner typologies and consist of 10 questions, each emphasizing the perceived importance of various benefits that may be important to the forest owners. All questions were rated by the respondents using an ordinal Likert-type scale of 1-7 where 1 reveals the strongest motive corresponding to 'Very Important' and 7 reveals the weakest motive corresponding to 'Not Important' for owning the land. The distribution of answers is given in Table 3.1. The responses to questions related to Non-timber Forest Products (NTFP) and Firewood (9f and 9g) were removed from further analysis due to their small variance as most of the respondents gave similar ratings to these questions. Question related to the perceived importance of having the woodland as part of their home or vacation home (part of question 9) was also not included in the analysis due to dissimilarities in the framing of this question across different versions of the questionnaire used in the three different states for the years 2002 to 2004. In effect we used 8 attitudinal questions (9a to 9j excluding 9f and 9g) for further analysis.

Table 3.1 Survey questions from NWOS used for cluster analysis

		Percentage of answers							
Question no.	Question	1	2	3	4	5	6	7	
		Very Important	……	……	……	……	……	Not important	No answer
9	"People own woodland for many reasons: How important are the following as reasons for why you own woodland?"								
9a	To enjoy beauty or scenery	46.23	13.97	10.83	10.38	4.18	1.72	4.71	7.99
9b	To protect nature or biologic diversity	36.07	14.04	12.47	12.62	5.38	4.78	4.33	10.31
9c	For land investment	50.78	11.58	10.75	6.87	3.29	2.02	6.87	7.84
9d	For privacy	38.31	9.86	8.14	7.77	4.26	4.26	15.91	11.50
9e	To pass land on to my children or other heirs	58.18	12.02	8.14	6.65	2.69	1.27	5.75	5.30
9f	For cultivation/collection of non-timber forest products	7.54	4.63	6.35	11.80	7.24	11.95	37.27	13.22
9g	For production of firewood or biofuel (energy)	4.41	2.91	6.05	8.66	7.47	14.64	42.94	12.92
9h	For production of sawlogs, pulpwood or other timber products	44.51	13.74	10.90	7.84	3.29	2.84	10.31	6.57
9i	For hunting or fishing	35.10	14.34	12.77	11.05	3.81	3.36	12.32	7.24
9j	For recreation other than hunting or fishing	19.64	9.26	11.13	12.92	6.42	6.87	22.48	11.28

Principal Components Analysis (PCA) is the most important statistical routine for dimensional reduction and seeks to transform a larger set of correlated variables into a smaller set of uncorrelated variables or factors without losing much information. PCA with varimax rotation was used to reveal the latent constructs (factors) of forest owner motivations based on the 8 questions mentioned above by utilizing the variance-covariance matrix of responses. Varimax rotation[17] was used to facilitate interpretability of factors by maximizing the variance of loadings (correlation coefficients between the factors and the variables) on each factor for use in the subsequent clustering procedures. In other words Varimax solution ensures that each factor tend to have either large or small loadings of any particular variable. Items loading 0.4 or greater (Garbin and Teng, 1988) on a factor were used to interpret the factors. Two factors were identified as *economic* and *non-economic* with the former denoting a strong timber interest related to timber harvests and land investment and the latter denoting the non-timber amenity values (biodiversity, aesthetics, recreation) of the forest perceived as the most important reasons for owning the forestland by the landowner. The overall Kaiser-Meyer-Olkin (KMO)[18] measure for factor suitability was 0.72 confirming the factorability of the indicator variables (NWOS questions). The two factors together explained 55% of the variance in the responses to the reasons for owning forestland by the landowners. Reliability analysis was conducted by computing Cronbach's alphas for each factor

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[17] Varimax is an orthogonal rotation of the factor axes to maximize the variance of squared loadings of a factor (column) and all the variables (rows) in a factor matrix (see Table 3.2).

[18] KMO is a measure of sampling adequacy and evaluates the appropriateness of the correlation matrix for factoring. KMO values should be greater than 0.6 for a satisfactory factor analysis (Tabachnik & Fidell 2001).

which ranged from .64 to .72, suggesting internal consistency for each of the factors extracted. Finally, a scores matrix of the order N × 2 where N (1339) denotes the total number of NWOS respondents with a score on each of the 2 factors was computed by taking each respondents standardized score on each variable, multiplied by the corresponding factor loading of the variable for the given factor, and summing these products. The factor scores describing owner motivations to manage their forestland were used as criterion variables for the cluster analysis. The factor loadings denoting the correlations between the variables (rows) and factors (columns) are given in Table 3.2.

The pattern loadings of the two factors are given in Table 3.2 below and represent the common variance in each of the variables (NWOS questions) explained by the factors.

Table 3.2 Factor loadings representing the correlations between factors and the variables

	Non-economic	Economic
Aesthetics	0.76	0.01
Biodiversity	0.62	0.00
Recreation	0.65	0.07
Privacy	0.65	–0.03
Legacy	0.26	0.27
Hunt	0.50	0.31
Timber	–0.07	0.83
Investment	0.03	0.46

3.4.2.1 Cluster Analysis

In order to get meaningful groups of family forest owners based on their motivations for owning and managing their forestland, NWOS data was subjected to clustering analysis using the factor scores on the two factors extracted for each respondent. Since all the clustering routines available through various mathematical software packages are biased towards identifying clusters with certain characteristics, once the data are input it is necessary to identify the algorithm which gives the best interpretable results and then test cluster validation. As a first step to clustering, the SAS procedure CLUSTER explored various hierarchical methods such as single linkage, complete linkage, average linkage, centroid and Ward's method (SAS 2004, p. 955) to determine the best method for clustering the data. The hierarchical clustering method is exploratory in nature and assumes no *a-priori* information about the number of clusters. To get landowner clusters of reasonable proportions and exclude the possibility of producing groups that were too small, Ward's minimum variance method was used. This method is based on least-squares criteria and tries to minimize the within-cluster sum of squares, thus maximizing the within-cluster homogeneity. The 'agglomerative dendrogram' that provides a visual representation of the step-by-step hierarchical clustering process wherein at each step the two closest clusters are merged into one bigger cluster, was not very useful to evaluate the cluster solution owing to the cumbersome interpretation of a large number of observations (respondents). Based on some of the most widely used statistics like root-mean-square standard deviations (RMSSTD), semi-partial R-squared (SPR) and R-squared (RS) a three cluster solution was found to be appropriate and supported our initial hypothesis.

Using a non-hierarchical (K-means) method to sort the observations to the nearest centroid through the procedure FASTCLUS[19] in SAS we found similar results compared to the hierarchical method. The results discussed in the next section were obtained by the non-hierarchical clustering routine. 254 incomplete observations (no response on at least one of the 8 questions on reasons for owning forestland from Item 9 of the NWOS) were excluded from the cluster analysis and this resulted in reducing the number of observations to 1085 from 1339.

The three clusters were named *timber* (319 owners), *non-timber* (233 owners) and *multiple-objective* (533 owners). The mean response for all the questions used in the cluster analysis by cluster groupings is plotted in Figure 3.2. As can be seen in Figure 3.2 below, the *multiple-objective* owners valued both the economic and non-economic use of the forest as the driving forces for owning forestland. Surprisingly the *multiple-objective* owners gave higher importance to the non-economic reasons than the *non-timber* cluster and also a higher importance to the economic reasons than the *timber* cluster. It is evident that this owner group, which includes the largest percentage of all family forest owners (49.1%) are strongly motivated by both consumptive (hunting, timber harvest) use values and the non-consumptive (aesthetic beauty, biodiversity) use values equally. The *timber* cluster (29.4%), as expected, had only timber management and land investment as strong motivating factors behind their forestland ownership. *Timber* cluster owners are typically concerned about the consumptive use value of their forestland unlike the *non-timber*

[19] FASTCLUS in SAS uses a nearest centroid sorting iterative method where a set of points known as cluster seeds is selected as the first guess of the mean of the clusters and each observation is assigned to the nearest seed to form temporary clusters, the seeds are then replaced by the seeds of the temporary clusters in an iterative manner until no further changes occur in the clusters (for detail see SAS 2004).

cluster (21.5%) owners who value the non-consumptive uses of their forestland such as aesthetic values, biodiversity, recreation and privacy.

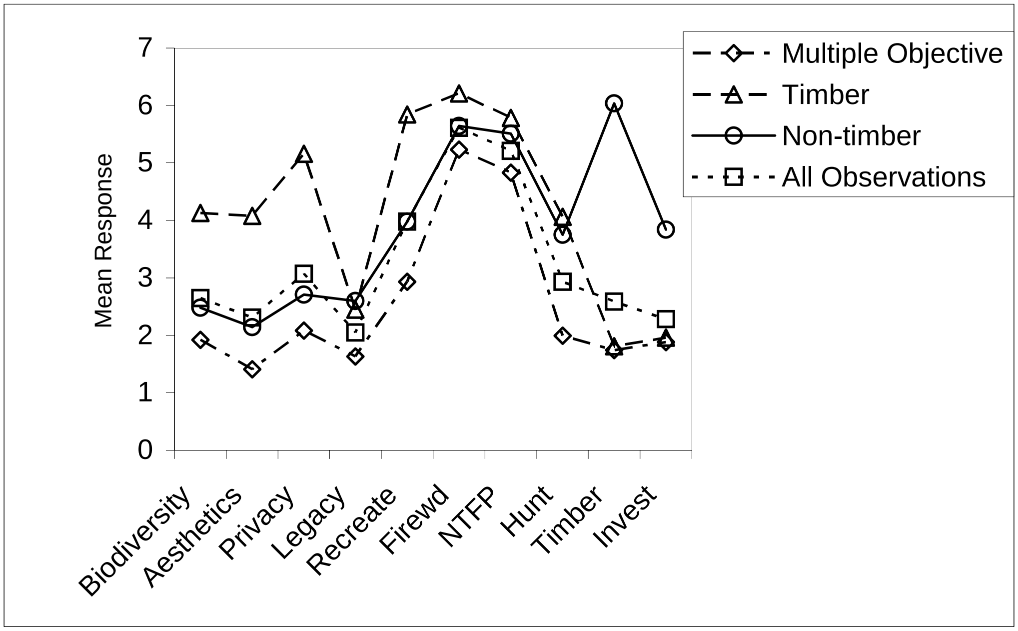

Figure 3.2 Mean response of reasons for owning forestland by cluster group, 1 denoting 'Most important' and 7 denoting 'Least important'

The socio-demographic and forest characteristics of the three types of family forest owners are described in Table 3.3. Responses reveal that the *non-timber* cluster owners were the least educated and least wealthy in comparison to the *multiple-objective* cluster owners and the *timber* cluster owners. The majority of the *non-timber* type of owners was retirees though the mean age of all the owners across all ownership types was greater than 60 years, suggesting that the family forests are going to change hands and new owners are going to replace the present surveyed owners shortly. It remains to be seen whether these new owners will have similar motivations as their predecessors or if they will act differently. The longest average tenure of forestland ownership lies with the *timber* cluster owners reflecting that profit motivated owners generally have managed the same forestland for a longer time as compared to owners in other clusters. It also reflects that timber management is a long term decision of the owner belonging to the *timber* cluster when compared to maintaining forestland primarily for non-timber uses by the owners of the *non-timber* cluster. As expected the timber cluster tended to own the largest tracts of forest with a mean size of 1857.9 acres and the *non-timber* cluster owned the smallest sized tracts of 384.5 acres on an average. It suggests that owners of larger tracts are more likely to manage for timber quite different from owners of smaller parcels. The *timber* cluster owners were also found to have strong linkages to farming and owned on an average 412 acres of farmland. The *multiple-objective* owners, on an average, owned slightly more farmland with an average farm size of 444.7 acres. Not surprisingly, the *non-timber* group with strong non-timber ownership objectives had the smallest mean farm size of 229.7 acres. There was a stark contrast in the percent of owners belonging to the *timber* cluster (52.3%) who had leased their land relative to owners within the *non-timber* cluster (19.7%). Further empirical evidence amongst the single ownership objective groups (*timber* and *non-timber*) as expected reflected the difference in the behavior related to timber management with a sharp difference in the percent of owners within each group who had written management plans, had harvested timber or had done some site preparation to plant new trees. The majority of owners classified in the *timber* cluster had inherited their forest property while the *non-timber* owners were least likely to have inherited their forestland. This coupled with the fact that these owners have the maximum tenure show that *timber* motivated owners have high legacy values relative to the *non-timber* type of ownership. However, owners belonging to the *multiple-objective* ownership class had relatively stronger preferences for both timber and non-timber products relative to the other two owner types (see Figure 3.2).

Table 3.3 Socio-demographic and forest characteristics of family forest owners by cluster

Characteristic	Multiple-objective	Timber	Non-timber
Mean age (yrs)	61.5	64.2	62.2
Men (%)	74.1	66.1	75.9
Mean duration of ownership (yrs)	28.6	31.2	22.4
Income (1000$)	79.4	78.3	71.4
Education	4.2	4.3	3.8
Retired (%)	36.7	42.9	45.5
Mean forest area (ac)	1345.3	1857.9	384.5
Farm area (ac)	444.7	411.6	229.7
Management plan (%)	32.1	25.7	10.3
Site preparation (%)	47.8	43.3	12.9
Harvest (%)	89.3	86.2	56.6
Leased (%)	44.1	52.3	19.7
Inherit (%)	49.3	56.7	27.5

3.4.2.2 Cluster validation

While classification procedures using cluster analysis have been applied to family forest owners in a number of studies (Kurtz and Lewis 1981, Marty 1983, Kluender and Walkingstick 2000, Kittredge 2004, Kendra and Hull 2005), none of the studies reported results of any empirical cluster validity test. Based on the 5-step cluster validation technique as suggested by Lattin et al. (2002) we performed a validation test on the NWOS clustering results (Table 3.4). According to this technique at the first step the data were randomly split in the ratio 1:1 using the RANSPLIT macro in SAS. The two samples thus formed are referred to as the calibration and the validation samples. At the second step the calibration sample was used for hierarchical cluster analysis and the appropriate number of clusters and their centroids were determined. In the third step the cluster centroid from the second step was used to assign each observation from the validation sample to the nearest centroid using non-hierarchical cluster analysis and the cluster solution was saved. In the fourth step the validation sample was used to perform a similar hierarchical cluster analysis as in the second step and the results were saved in a SAS database. Finally the cluster solutions obtained from the step-3 and step-4 were compared and a confusion matrix (Table 3.4) depicting the percent of observations in each of the three cluster groups incorrectly classified into another group was created. As can be seen, the percent-misclassification was pretty low and most of the observations that were clustered at both step-3 and 4 of the validation routine also were found to be in the same cluster group with the percent of correct classification for each of the three types of landowner to be above 95% (see table 3.4).

Table 3.4 Confusion matrix for cluster validation

	Multiple-objective	Timber	Non-timber	% Misclassification
Multiple-objective	322	*	8	2.4
Timber	5	181	*	2.7
Non-timber	*	2	189	1.05

* Denotes null or 0 number of observations

3.5 Conclusion

Our study supports the presence of three groups of family forest owners in the three Southeastern states of AL, GA and SC as discussed in the theoretical model on landowner behavior above and also as reported by Butler (2005) in his study of family forest owners in five southeastern states. It also emphasizes the need to differentiate family forest owners into smaller well-behaved homogeneous entities. Contradictory to Kendra and Hull’s (2005) recent study on new owners in Virginia, the bulk of landowners in our study were found to be motivated strongly by the profit motive either through timber harvests as a source of income generation or choosing forestry as a better land investment option. As reported above, landowners have different objectives and motivations for managing their forestland and identification of those may be critical to developing better informed policy prescriptions. Policies can be targeted towards each owner group according to their needs and interests and thus policy implementation can be made more efficient. For example, timber harvests for owners within the *non-timber* group may be for wildlife habitat or to maintain a healthy forest which is quite different than for economic reasons.

The *multiple-objective* ownership type was found to be the largest group with almost every 1 out of 2 family forest owners in the sample population belonging to this category. These owners derive utility from both economic and non-economic uses of the forest and also potentially could be the ones targeted by policy makers and resource managers to enhance their production of timber or non-timber outputs since they are not devoted to any single management objective unlike owners in the *timber* and the *non-timber* clusters.

The above work is by no means complete and further analyses of the data by integrating the detailed forest characteristics, which complement the ownership NWOS data, along with linkages to the socio-economic Census data, could produce important information on family forest owner behavior. Also a large number of observations (223) excluded from the analysis due to incomplete responses warrants a closer look to check if there are enough similarities amongst them to be classified as a separate cluster or not. Finally, the average age of family forest owners is in the sixties and it remains to be seen if the future change of ownership will be associated with changing owner attitudes and motivations or not. This also suggests the dynamic nature of human behavior and one on which studies need to be updated from time to time.

This study is based on the psychological responses of landowners to factors they think motivate them most for owning forestland and the results should be explored further to see if landowner attitudes are supported by their actual behaviors. In other words to draw conclusions, it is necessary to check if landowners do what they say or are the responses merely what landowners perceive as ideal.

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CHAPTER 4

DISCRIMINATING FAMILY FOREST OWNERS: A NON-PARAMETRIC APPROACH

4.1 Introduction

Who owns the forest? Ownership patterns have changed dramatically over the last 20 years, with Forest Industry (FI) selling most of its holdings to Timber Investment Management Organizations (TIMOs), Real Estate Investment Trusts (REITs) and private individuals, parceling their holdings to more, smaller ownerships. Within the last decade, while forest industry was divesting itself of its forest holdings, the number of family forest owners[20] nationwide rose by 11%, from 9.3 million to 10.3 million, and these owners now own 42 % of the nation's forestland (Butler and Leatherberry, 2004). Given their large numbers and the expectation that their numbers will continue to increase, a closer look at their motivations and reasons for owning forestland is warranted. Previous research has often treated family forest owners as a single homogeneous class when trying to analyze how they might manage their forests in the future.

But given their diversity in terms of the characteristics of the forest properties they hold, their economic and social surroundings and their personal histories and characteristics, this assumption of homogeneity may, in reality, be totally inappropriate.

[20] Family forest owners are defined as 'family forests include lands that are at least 1acre in size, 10% stocked, and owned by individuals, married couples, family estates and trusts, or other groups of individuals who are not incorporated or otherwise associated as a legal entity' (Butler and Leatherberry 2004).

We investigated the notion that family forest owners have diverse objectives and that their subjective preferences for managing their forest for timber (primarily for income) and non-timber amenity values are wide-ranging (Majumdar et al 2006) and inferred that family forest owners can be grouped into three motivational types[21] namely, *Timber*, *Multiple-objective* and *Non-timber*.

The objective of this paper was two-fold, first to identify the characteristics that discriminate best the three above mentioned owner types using discriminant analysis procedures and second to develop a classification scheme that will help in predicting the objectives of new landowners given the vector of the discriminating variables. The results of this study will be helpful in making a connection between the policy makers and the family forest owners to help develop effective policy prescriptions and educational programs targeting at the forest stewardship goals of the landowner. Also, information on the implications of our research for future timber availability will benefit policy makers interested in finding ways to insure future timber supplies are sustained at current or enhanced levels.

4.2 Literature Review

A number of studies have looked into the family forest owners' heterogeneous motivations to own forestland and have explored the presence of owner typologies (Young and Reichenbach 1987, Gramann et al. 1985, Kulluvainen et al 1996, Kluender and Walkingstick 2000, Kendra and Hull 2005, Butler 2005, Finley et al. 2006), but apart from characterizing the landowner groups based on socio-demographic attributes and

[21] For details of the data, techniques used for grouping the family forest owners of the southeast refer to the earlier work by Majumdar et al, 2006.

attributes of their forests few of the studies have actually investigated the differences between landowner groups subject to their exogenous social and economic environment. This article investigates how the *Timber*, *Multiple-objective* and *Non-timber* family forest owners in the Southeast differ from each other by linking their decision environment, which includes their social and economic surroundings, to their group membership, with a goal of being able to predict new landowner membership into one of the ownership categories. The multivariate discriminant function (DF) analysis technique was used to evaluate the predictive power of the explanatory variables. DF has been recently used in a number of studies related to private forest landowner behavior, for example, Arano et al. (2004) in their study of 829 Mississippi forest landowners consisting of two group, *non-regenerators* (402) and *regenerators* (427), used canonical discriminant function analysis to discriminate the owner groups based on ownership characteristics, landownership characteristics, attitudes towards timber investment, awareness of assistance programs and attendance in educational programs. Finley et al. (2006) used multiple discriminant analysis to link the association of the predefined groups of Massachusetts private landowners, namely, *general cooperators*, *conservation cooperators*, *neutralists* and *non-cooperators*, to forestland ownership reasons, attitudes and actions towards forest management and perceived barriers to cooperation. Though the studies mentioned above help in identifying factors or variables that best discriminate between the private landowner typologies identified, they do not report the classification results and so their reliability in terms of predicting landowner behavior is low. Greene and Blatner (1986) successfully classified nearly 80% of the respondents in a study of Arkansas private forest landowner groups, *timber managers* and *nonmanagers*, based on a set of 47 variables related to reasons for owning forestland, owner characteristics, forest characteristics and their attitudes towards forest management. This study suggests that the discriminating variables can be used to predict group membership, but since the entire set of variables comes from the survey instrument administered to the respondents, it is not possible to predict group membership for a new landowner who has not been administered the survey. This also reveals the importance of exogenous discrimination of landowner groups (where all the discrimination variables are exogenous, and not personal attributes of individual landowners). The objective of this study was to be able to use easily available secondary information on new landowners from sources other than the primary National Woodland Owner Survey[22] (NWOS) and predict their membership to one of the landowner groups established using NWOS. This requires first to identify such exogenous variables that can discriminate the three family forest landowner groups (Majumdar et. al. 2006), *timber, multiple-objective* and *non-timber* identified, and second to test the accuracy levels of the classification for predicting landowner behavior in the future. Given their increasing numbers and the forestland acres they manage, family forest owners have become increasingly important stewards of productive timberland in the South. Thus it is important to critically examine their motivations for managing their land either for timber and/or non-timber forest products.

[22] For details on the NWOS survey design, implementation and analysis methods see Butler et al. (2005)

4.3 Data and Methods

This paper involves multivariate discrimination procedures of three predetermined family forest owner types, *multiple-objective* (765 respondents), *non-timber* (292 respondents) and *timber* (459 respondents). The three groups of landowners identified from NWOS was linked to the Forest Inventory and Analysis[23] (FIA) data on the forest plots owned and managed by the family forest owners. Multiple conditions (FIA condition[24]) on each FIA plot resulted in landowners who had multiple conditions in their forest plot to be represented multiple times and so each observation (landowner) was weighted by the proportion of the plot that the condition represented in the analysis. This grouping of family forest owners in Alabama, Georgia and South Carolina, is based on responses to the NWOS obtained during the period 2002-2004. The landowner clusters were based on the importance they assigned to various reasons for owning forestland, ranging from timber and investment objectives to non-timber objectives such as biodiversity, aesthetics, hunting and recreation.

4.3.1 Data

The data consists of information on the socio-demographic, economic and bio-physical characteristics of each landowner belonging to one of the three family forest ownership types and was taken from various sources. The bio-physical data came from the FIA forest plots owned and managed by the family forest owners and included

[23] FIA forest resources inventory collects forest resources data annually from a sample of standard plots each representing roughly 6000 aces in the east, the social counterpart of the FIA forest resource inventories is the NWOS which is conducted on a sample of private forest owners of FIA plot already inventoried

[24] FIA Condition represents the multiple conditions and is defined by heterogeneity in reserved status, owner group, forest type, stand-size class, regeneration status and stand density within FIA plots (for details on FIA data description and collection methods see (Alerich et al. 2004)).

variables such as slope (SLOPE), average stand age (AGE), volume per acre (VOL), diameter per acre (DIA), distance to the nearest paved road (DIST), forest type (FT) (either pine, hardwood or mixed hardwood), site quality (SITE), physiography (PHYSIO), and tree biodiversity indices[25] characterizing forest management heterogeneity amongst the owner types. The socio-demographic and economic data were incorporated in the study from linkages of the Census Bureau data with the FIA plots. To represent the decision environment related to economic and socio-demographic factors the variables included were real median household income (INC), population gravity index (PGI)[26], pulpmills gravity index (MGI)[27] and population density (PD). The SAS procedure STEPDISC was used to select the variables that best discriminated the three groups of landowners and from the large pool of variables mentioned above the ones selected were, PGI, INC, PD (demographic and economic) and AGE, SLOPE, DIST, SITE and FT (bio-physical characteristics). The sources and the description of all the variables used in the discriminant analysis are given in Table 4.1.

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[25] Three indices were created to reflect the biodiversity of tree species in the landowner forest plot namely Shannon's index, Simpson's index and Richness

[26] PGI was calculated by linking landowner forest parcel location with the census demographic data on populated places as : $PGI_K = \sum_p \frac{P_p}{D_{kp}^{\;2}} \forall P : D_{kp} \leq 100km$ Where P_p is the population of census populated place p and D_{kp} is the distance between FIA plot k and populated place p

[27] MGI was calculated by linking the FIA plot to the pulpmills located within the radius of 200km around the forest plot and was calculated as: $MGI_k = \sum_m \frac{M_m}{D_{km}^{\;2}} \forall M : D_{km} \leq 200km$ Where M_m is the pulping capacity in million cords of pulpmill M and D_{km} is the distance between FIA plot k and pulpmill m

Table 4.1 Data sources and their descriptive statistics

Variable	Description	Source	Mean	Std. dev
PGI	Number of persons/Km^2 around each FIA plot within a 100km radius	FIA plot and Census Bureau	522.34	1432.23
INC	Median household income by county in $$	Economic Research Services (ERS) unit of USDA	32852.98	7164.54
POPDEN	Number of persons per square mile of county land area	Census Bureau	106.96	179.34
DIST	Euclidean distance from FIA plot center to the nearest improved road	FIA plot	4.22	1.44
SLOPE	Angle of slope in percent	FIA Condition	6.69	9.26
FT	Forest type having value of 1 for softwood, 2 for mixed hardwood and 3 for hardwood	FIA Condition	2.01	0.92
AGE	Average stand age	FIA Condition	31.87	23.86
SITE	Site productivity class code taking values from 1 to 6 with 1 representing the best site	FIA Condition	4.41	0.90

4.3.2 Discriminant Analysis

Discriminant Analysis (DA) is a statistical technique that allows the researcher to study the differences between two or more groups of objects with respect to several variables simultaneously (Klecka 1988). The goals of DA are to classify cases into one of the several mutually exclusive groups on the basis of various characteristics, to establish which characteristics are important for distinguishing amongst the groups, and to evaluate the accuracy of the classification. The aim of DA in this study was to investigate the accuracy of classifying a landowner into either a *multiple-objective* or a *non-timber* or a *timber* motivated group. The two assumptions of multivariate normality (tested using the Mardia's Kurtosis and Skewness statistical tests) and homogeneity of variances (tested using the SAS procedure DISCRIM with POOL = TEST option) for parametric discriminant analysis was conducted (see Table 4.2) and results suggested deviations from both the assumptions.

Table 4.2 Multivariate Normality and Homogeneity of variance-covariance test result

Test	Chi-square statistic	p-value
Mardia's Skewness[a]	197.6	<0.0001
Mardia's Kurtosis[a]	328.5	<0.0001
Levene Homogeneity[b]	338.8	<0.0001

[a]H_0: Multivariate normality
[b]H_0: Homoscedasticity

An alternative to linear discriminant analysis (used when both the normality and equal variance-covariance matrix assumptions are fulfilled) or quadratic discriminant analysis (used when the homogeneity assumption) or Fisher's discriminant analysis (used when the normality assumption does not hold) is non-parametric discriminant analysis and logistic regression analysis. It is unusual to find examples where researchers consider the statistical limitations and assumptions required for parametric techniques. In these instances, it is difficult to know whether the predictions are reliable. Because the primary goal of this paper was prediction of landowner's membership into one of the predetermined groups based on a vector of predictor variables and the relevant assumptions for linear discriminant analysis could not be met, the non-parametric analytical technique was adopted.

4.3.3 K-nearest neighbor method

K-nearest neighbor classification (KNN), also known as nearest neighbor discriminant analysis, was introduced by Fix and Hodges (1951) and is based on distances from 'immediate neighbors' eliminating the need for a probability density estimation based on some distribution assumption. It is used to predict the response of an observation using a non-parametric estimate of the response distribution of its *K* nearest (i.e., in predictor space) neighbors. Consequently, KNN is relatively flexible and unlike traditional classifiers, such as discriminant analysis and generalized logit models, it does not require an assumption of multivariate normality or a strong assumption implicit in specifying a link function (e.g., the logit link which assumes the distribution of the dependent variable to be within the exponential family of distributions, such as normal, Poisson, Binomial, gamma). KNN classification is based on the assumption that the characteristics of members of the same class should be similar and thus, observations located close together in covariate (statistical) space are members of the same class or at least have the same posterior distributions on their respective classes (Cover and Hart 1967). To decide which group a test case belongs to, SAS calculates the squared distance (Mahalanobis distance) between the test observation and each remaining member of the training dataset and classifies based on majority of classes for the nearest (shortest distance) K-neighbors. To illustrate the point suppose an observation (landowner) whose group membership is not known *a-priori* has attribute vector $\mathbf{x}$ and $\mathbf{x}_1$, $\mathbf{x}_2$, $\mathbf{x}_3$, $\mathbf{x}_4 \ldots$ $\mathbf{x}_n$

are the attribute vectors of 'n' landowners who are already assigned to a group '*i*'. The squared distance between any two observations can be estimated as

$d_i^{\,2}(\mathbf{x},\mathbf{x}_1) = (\mathbf{x}-\mathbf{x}_1)'\mathbf{V}_t^{-1}(\mathbf{x}-\mathbf{x}_1)$ (Distance between the observation vectors $\mathbf{x}$ and $\mathbf{x}_1$)

Based on the squared distance defined above and the specified parameter '*k*', a positive integer, which denotes the number of nearest neighbors to be considered, '*k*' observations that are closest to $\mathbf{x}$ are identified. $\mathbf{x}$ is assigned to the group that the majority of the '*k*' nearest neighbors belong to. For example, in Figure 4.1 below, a new member '**X**' will be classified as 'White' when *k*=1, 'Black' when *k*=5 and cannot be classified based on majority votes when *k*=10.

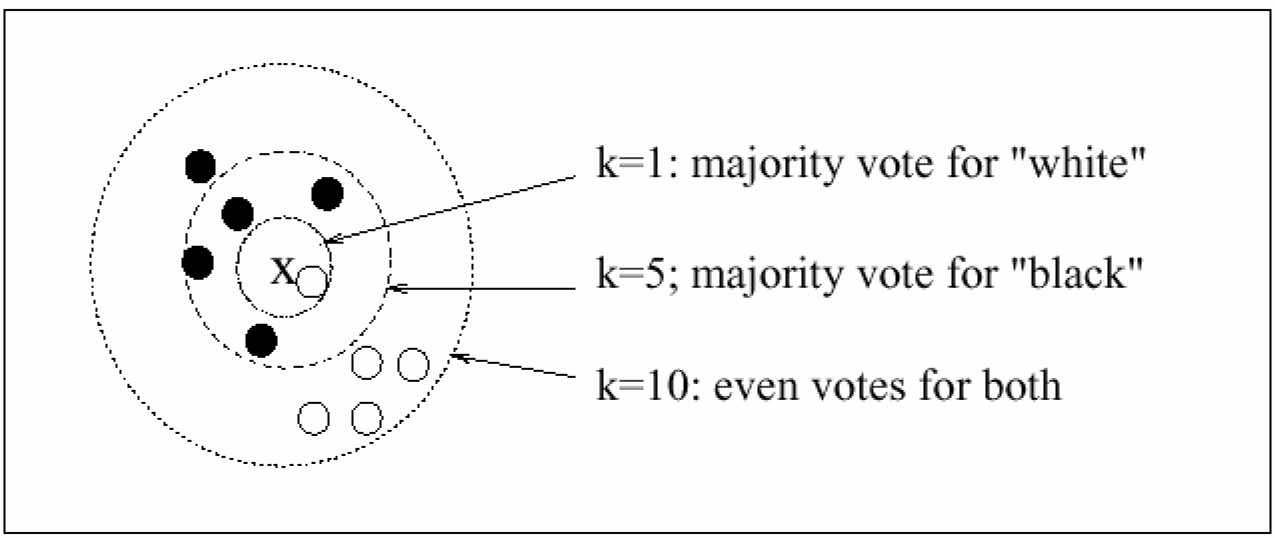

Figure 4.1 K-nearest neighbor classification based on k=1 or k=5 or k=10

4.4 Results

This study focuses on whether it is possible to predict group membership of family forest owners in the southeast using variables which are not collected using a survey of landowners, in other words, is it possible to assign a new landowner to a broader group based on management objectives *ex-ante* to acquiring primary data from the landowners. The summary statistics of the variables selected as discriminators (using step-wise selection SAS procedure STEPDISC) between the three landowner groups namely, *multiple-objective*, *non-timber* and *timber* according to their preference for producing either both, non-timber or timber is given is Table 4.1. The socio-economic (INC, DIST), demographic (PGI, POPDEN) and bio-physical characteristics (SLOPE, SITE, AGE and FT) describing the three groups of landowners can be used to classify a new (previously unclassified) landowner into one of the groups. KNN classification performance is evaluated using two accuracy measures generated as part of the output from running the SAS procedure DISCRIM. These are referred to as the apparent error rate and the cross-validation error rate. Percentage of correct classification within each group (cluster) and the whole population based on predictions of KNN classification are reported in Table 4.3. Since in this case the same input data is used to define and evaluate the classification criterion, the resulting error-count estimate has an optimistic bias (SAS 2004, p. 1163). One way to reduce the bias is use the *one-leave-one* (Lachenbruch and Mickey 1968) option to classify each observation based on the discriminant function computed from all other observations (Cross-validation). Results are reported in Table 4.4. In order to identify the misclassifications we constructed the confusion matrix for the one-leave-one cross validation technique in Table 4.5. In a confusion matrix each row represents a true class and each column represent the predicted class and results show (Table 4.5) that while the average accuracy of prediction across all the landowner groups was 68%, it was 74.4%, 64.5% and 58.6% for *multiple-objective*, *timber* and *non-timber* owners respectively.

Table 4.3 Classification results for the apparent-error-rate KNN method

	Percentage Correct			
k	multiple-objective	non-timber	timber	Total
2	86.7	78.4	81.7	83.6
3	74.4	58.6	64.5	68.3
4	68.9	45.9	53.4	59.8
5	76.6	46.9	54.9	64.3
6	77.2	44.9	52.9	63.6
7	78.8	41.1	49.7	67.7
8	73.1	38.4	47.7	58.7
9	76.3	39.4	47.7	60.5

Table 4.4 Classification results for the one-leave-one cross validation KNN method

	Percentage Correct			
k	multiple-objective	non-timber	timber	Total
2	74.5	58.6	64.5	68.3
3	68.9	45.9	53.4	59.8
4	76.6	46.9	54.9	64.3
5	77.2	44.9	52.9	63.6
6	78.8	41.1	49.7	67.7
7	73.1	38.4	47.7	58.7
8	76.3	39.4	47.7	60.5
9	76.9	38.0	42.7	59.0

Table 4.5 Confusion Matrix of one-leave-one cross-validation method for *k*=2

	multiple-objective	*non-timber*	*timber*	*Other*	Total
multiple-objective	569	70	120	6	765
non-timber	77	171	43	1	292
timber	118	41	296	4	459
Total	764	282	459	11	1516

Accuracy measures (Table 4.3 & Table 4.4) can be calculated in more than one way as advocated by Congalton (1991) who presented two methods as *users accuracy* and *producers accuracy*. *users accuracy* calculates correctly classed from the trace variable (diagonal elements of the confusion matrix (Table 4.5)) over the row total and provides indication of errors of case omission. Similarly *producers accuracy* is the calculation of correctly classed from the trace value over the column total. *producers accuracy* gives an indication of the accuracy of what the model was able to itself predict, whereas users accuracy relates how well the training data was discerned. Table 4.6 below presents the results of users accuracy and producers accuracy calculated from the leave-one-out cross validation results (Table 4.5) of KNN classification (*K*=2).

Table 4.6 Producers and Users accuracy for leave-one-out cross-validation method (*k*=2)

	producers accuracy			*users accuracy*		
	Classed	Column Total	Accuracy %	Classed	Row Total	Accuracy %
multiple-objective	569	764	74.5	569	765	74.4
non-timber	171	282	60.6	171	292	58.6
timber	296	459	64.5	296	459	64.5

Figure 4.2 & Figure 4.3 below are graphical representations of the correct percent of observations (landowners) that the discriminant analysis predicted they would be a part of for different values of k for the apparent error rate and the cross-validation methods respectively. As mentioned before, *k*=2 is the point where the figures (4.2 & 4.3) peaked consistently for all the landowner groups (except for the *multiple-objective* group of owners in the cross-validation method (see Figure 4.3) where it peaked at *k*=6)) suggesting the choice of the free parameter *k* in the model.

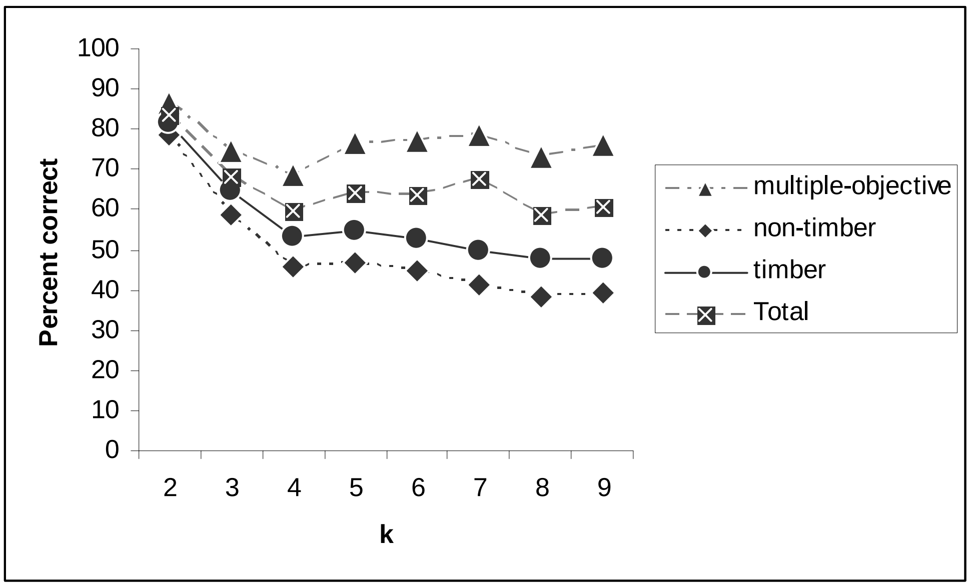

Figure 4.2 Graphical representation of apparent-error-rate accuracy of KNN by *k*

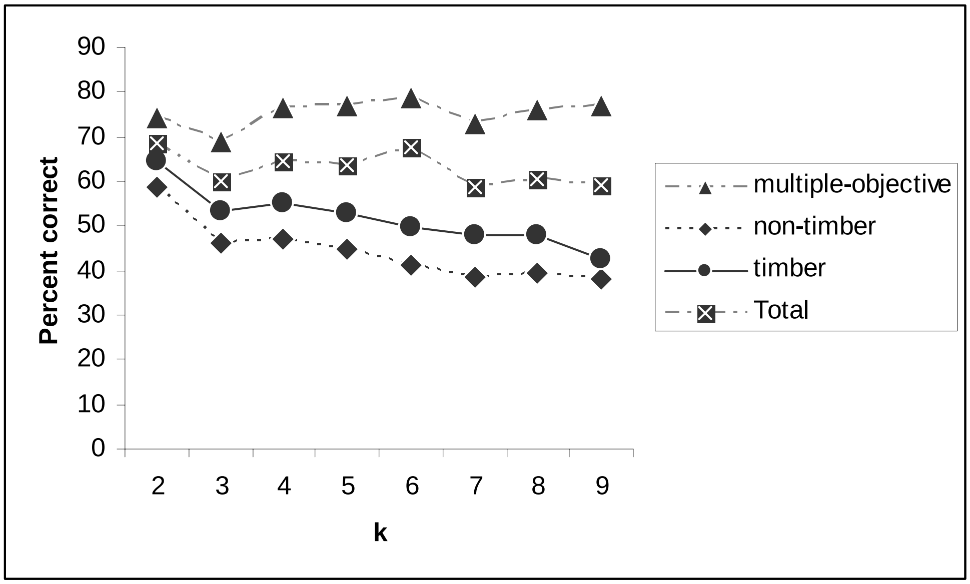

Figure 4.3 Graphical representation of one-leave-one cross-validation accuracy of KNN by *k*

4.5 Conclusion

This study indicates that landowners can be accurately classified into heterogeneous attitudinal groups (multiple-objective, non-timber and timber) using the non-parametric KNN technique. The high accuracy rate of classification (84% in apparent error rate and 68% in cross-validation) of landowner groups indicates a higher percent of accuracy than would be expected if they were due to chance alone. In other words, this means that the high prediction accuracy is not merely due to random occurrences that have happened by chance. We found that bio-physical (SLOPE, SITE, FT and AGE), socio-economic (INC and DIST) and demographic (PGI and POPDEN) variables had a strong association with landowner group profiles.

Examples of the use of discriminant analysis in landowner studies are sparse and have concentrated on searching for variables that discriminate owner groups, eg., timber managers vs non-managers (Greene and Blatner 1986), regenerators vs non-regenerators (Arano et al. 2004), cross-boundary cooperators vs non-cooperators (Finley et al. 2006). All of the above studies have neglected exploring the predictive component of discriminant analysis. Moreover these studies have resorted to differentiate landowner groups based on survey questions and so *ex-ante* prediction of non-surveyed landowners into one of the groups is beyond the scope of their work. Since all the variables used to develop the classification scheme in this study are known, *a-priori*, that is, before landowners on a FIA plot location are contacted for the NWOS, it may be possible to predict membership of a future landowner with known FIA and Census demographic attributes. This piece of information can also help design the NWOS survey to better focus on issues of interest to landowners and can help improve communications and development of effective outreach and educational programs. Given the increasing number of family forest owners and the increasing proportion of timberland they own and manage as an ownership class, this study can effectively help in estimating the different adjustment factors for diversely motivated landowner groups in order to more accurately project future timber supply.

To our knowledge KNN classification has not been used to study landowner behavior though the technique is relatively simple to implement especially since there is no need to meet the statistical assumptions inherent in parametric classification methods (e.g., variables characterizing the difference between the landowner groups must have multivariate normal distributions and equal variance-covariance matrix). Our study also extends research on ways to predict landowner behavior in the future by taking into consideration their diverse set of motivations and attitudes towards forest management instead of treating the family forest owners as a single homogeneous group.

We feel that in this paper we have just touched the ‘tip of the iceberg’ and it is necessary to explore in detail the diverse motivations of family forest owners and ways to differentiate them to be able to understand them, make a connection and develop in tandem with their needs specific educational programs to insure future timber and non-timber supplies from family forests at current or enhanced levels.

4.6 References

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