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MODELING TIMBER HARVESTS IN THE NORTHEASTERN UNITED STATES

A Thesis in

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by

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Abstract

Timber harvesting activity takes place for a variety of reasons. Environmental, social, and economic factors all influence where and when a harvest occurs. Using the FIA database and statistical modeling, our research has shown that there are factors statistically significant to a harvest at both the plot and tree level in the northeastern United States. These factors also vary with the proportion of basal area of timber removed in a harvest. Using logistic regression to examine these significant factors, we have determined that the value of standing timber has an effect on harvest probability at the stand level. At a tree harvest level, there is no significant relationship between harvesting decision and individual tree value. This may be due to the factors considered when a site is being considered for a harvest differing from those when individual trees are being selected. A significant difference also exists for harvests on private versus public land, with private owners tending to take larger, more valuable trees, but less overall stand volume. Diameter tends to be a strong predictor of harvest probability at both the plot and tree level, and suggests that there is an increasing harvest probability up to a maximum plot average or individual tree size, after which, the probability of a harvest decreases. Model variable statistical significance for volume/size metrics such as diameter and cubic feet is quite high. The inability to utilize strong explanatory variables to describe a large portion of the variation inherent in timber harvests is a problem that plagues similar studies, even at smaller scales, suggesting that more research needs to be done on what environmental, social, or economic variables influence timber harvests, and whether these factors are national or regional. In attempting to explain what significantly influences timber harvests with our models, we can statistically say that volume, size, and to a degree, value, are all factors influential to timber harvesting in the northeastern United States.

Table of Contents

List of Tables

List of Figures

List of Equations

Chapter 1 - Introduction

Timber harvesting in the United States is a 235 billion dollar a year industry (AFPA, 2016). It accounts for 53% of total tree mortality, as 13 billion cubic feet of standing timber are removed every year (US Forest Service, 2014). Yet very little research has been done on the decision-making processes by which trees are selected for harvest, as shown in articles as recent as Kittredge (2015). Are these decisions the product of silvicultural planning? When a harvest does occur, which trees are selected and why? Is the value of the tree a factor? These questions need to be answered in order to better understand and predict future management practices by forest owners, from the private woodland owner (PWO) of a few acres all the way to federally-held, multi-million-acre forests.

This research examines whether a variety of factors contribute to the probability of harvesting standing timber. A specific and new focus of the research is the effect of value on the probability of harvest. Statistics on specifically what species and size of trees have been harvested are also examined. The data used in this study are from a 22-state region in the northeastern United States, and are primarily from the Forest Inventory Analysis (FIA) database created by the United States Forest Service (USDA-FS). United States Census data are also used. FIA data are collected on 1/6-acre permanent plots that have been re-measured, in most cases, on a 5-year interval. FIA data were used for this study because the data offer the largest and only representative sample available of the condition of forests in the United States (http://www.fia.fs.fed.us/).

In addition to answering questions about harvest behavior, the motivation to model harvesting activity using FIA data also stems from a collaboration with Dr. Charles Canham of the Cary Institute that is focused on using the SORTIE model (Pacala et al. 1993) to project how future forest composition and conditions may be affected by forest pests, pathogens, and climate change. The project is funded by the United States Department of Agriculture Animal and Plant Health Inspection Service (APHIS). This work models the impact and spread of invasive forest species such as Asian Longhorn Beetle (ALB), Emerald Ash Borer (EAB), Hemlock Wooley Adelgid (HWA), and Beech Bark Disease (BBD). Adding the human component of forest change dynamics requires an examination of the factors that influence forest landowners' and managers' decisions to harvest standing timber and what they choose to harvest.

In order to model the probability of forest harvests, it is necessary to first define what we mean by the phrase "timber harvest." Does a harvest only occur when a large portion of a stand is removed? If the removal of even a single tree is considered a harvest, then are the factors that influence the decision to conduct a low volume removal the same as those that influence a high volume removal? How motivations vary among different types of harvests has not been well studied. This research examines this question explicitly by separating harvests into three categories: light thinnings (less than 20% of the basal area (BA) removed), medium-heavy thinnings (between 20% and 85% of the BA removed), and stand-replacing harvests (more than 85% of the BA removed).

Preliminary analysis for this research found that the vast majority of harvests that occur on FIA plots do not involve removing all the trees on the plot-condition; Canham et al (2012) described partial harvests as the norm, not the exception. Thus, in addition to understanding why a harvest might occur on a plot-condition, it is also important to evaluate the factors that motivate the selection of individual trees to harvest from a plot-condition when a harvest occurs. Thus, where harvest activity was observed to occur on an FIA plot-condition, a second step modeled the selection of specific trees to be harvested to evaluate what variables influenced those decisions.

The motivations behind timber harvesting have been studied in a variety of previous academic articles, though only a few previous studies focused on an area as large as the 22-state study area of this research (Butler and Leatherberry 2004; Canham et al 2013). Those studies both dealt with regional landowner behavior. Factors considered in past harvesting research have typically included both environmental and socio-economic variables. A variety of studies looked at price as a factor significantly influencing timber harvests (Adams et al., 1991; Buongiorno et al., 1988; Butler, 2005; Gong, 1998; Lönnstedt, 1997; Max and Lehman, 1988; Plantinga, 1998; Prestemon and Wear, 2000; Provencher, 1995; Rucker and Leffler, 1988; Schuster and Niccolucci, 1983), However, none of these looked beyond regional markets with limited price data, and none looked specifically at tree value. Many of the variables included in models in this paper were found to be significantly related to timber harvesting in previous studies. A unique contribution of this research is the inclusion of timber price data from many states covering a large region of the US.

The primary objective of this research is to statistically explore factors significant to forest landowners' and managers' harvesting decisions at both the plot and tree level, based on variables that are available in the FIA data or that can be easily linked to the FIA data, and by examining these variables at different removal intensities. In addition, when these harvests occur, the research examines what is taken. Another objective of this research was to develop prediction models of harvests on FIA plots using multiple variables obtained from the FIA database and other sources. Both goals were accomplished using logistic regression analysis to assess whether various plot attributes that can be derived from the FIA data (or external data that can be obtained for all FIA plots) are good predictors of whether or not the plot was harvested, what type of harvest was conducted, and whether tree attributes are good predictors of which trees were removed. Because FIA data contain limited socioeconomic and no attitudinal information about the forest landowners and/or managers, these factors could not be assessed in depth. On the other hand, the advantages of using FIA data for this study are the size and representativeness of the FIA data set, covering all owners and all forest types, and the wealth of factors that can be assessed using this data set.

Chapter 2 - Literature Review

The birth of modern statistics in the United States had its roots in agriculture (USDA, 2014), and as long as there has been a market for forest products, statistical work has been used to manage and optimize resources (Straka, 2009). Although timber production is the number one cause of forest tree mortality in the northeastern United States (Canham et al., 2012), timber growth rates are also fastest in those forests that are best managed (Beuter, 1976). The best managers of these harvest-focused forests typically tend to be high-income, multi-objective, non-industrial private forest owners (NIPFs) and industrial forest land owners, both of whom generally have a continuing financial investment in these stands (Berck, 1979; Joshi, 2007; Lönnstedt, 1998; Prestemon and Wear, 2000). However, with only 5% of NIPFs having a management plan in place and the majority of those landowner properties not being held for timber production, using ownership as an indicator of best management practice is not recommended (Birch, 1996; Dennis, 1989). Past harvest by an owner significantly increases the probability that they will harvest again in the future (Larsen and Gansner, 1972), and given enough time, all stands tend to enter into some form of management (Stone, 1970). Ecologically, timber harvest and management directly affect wildlife and habitat fragmentation, so it is important to understand where and what will be harvested (Hof and Joyce, 1993).

History

Early research on harvest choice includes a United States Forest Service report by Ferguson (1958) that examined Pennsylvania forests by ownership class and distribution. In quantifying what resources were available, this paper laid the ground work for further investigation of the forest industry as businesses sought to better utilize timber products. Stone (1970) was arguably the first to supplement the Ferguson (1958) report to break down who was utilizing timber and why, though this early research had more to do with defining why harvests occur and less to do with optimization.

Timber RAM (Navon 1971) led to the use of linear programming optimization models to maximize yield or net present value for optimal timber management. Statistical models at the time used independent landowner surveys, and employed chi-square analysis to assess factor significance. Larsen and Gansner (1972) worked to identify characteristics of those who owned land and harvested it and established model criteria for the majority of future research. Their approach was later used by both Beuter (1976) and Kingsley et al. (1977), who conducted their own surveys across varying US regions.

Binkley (1981) utilized a logistic regression model coded for harvest vs. non-harvest that shifted research to focus on factor interpretation. This generally marked a turning point away from simple optimal harvest volume prediction based on Markov chain, linear optimization, and general regression such as that used by Johnson and Scheurman (1977), Tedder et al. (1980), Schuster and Niccolucci (1983), and others, towards a more complete understanding of basic factors influential to harvest. That focus added factors of interest related to landowner characteristics from those related to productive capacity, species composition, harvesting price, and discounting rates. For example, Larsen and Gansner (1973) examined landowner characteristics such as income, land holding size, and landowner occupation. Following Ferguson's (1958) grouping of owners as either public and private and Stone's (1970) division of private groups into NIPFs and industry in the early 70's, work on owner-level factors continued to further define harvest and management choices by different ownership types using detailed landowner surveys.

Barlow et al. (1998) were the first to utilize the US Forest Service's Forest Inventory Analysis (FIA) data to test variables in a logistic regression model to predict probability of harvest. The FIA is a national survey of permanent forest plots that are measured at regular intervals (USDA-FS, 2014). This data set allowed for an examination of harvests on individual plots, which were then linked to site attributes. Whereas previous studies focused on landowner factors from surveys, use of FIA data allowed for an examination of the relationship between site attributes and the probability of harvest. Follow-up work on the significance of these environmental factors included Reams and McCollum (1999) and Prestemon and Wear (2000).

In the mid 2000's, the focus turned to classifying NIPF owners into categories by the variables that defined them, such as income, ownership size, employment type and status, ownership purpose, and others (Favada et al., 2009; Hoyt and Hodges, 2010; Majumdar et al., 2008). Given that industrial owners tend to harvest based on timber economics and market activity (Kuuluvainen et al., 1996), the focus of initially classifying NIPFs was on those whose irregular harvesting patterns made it difficult to determine when larger volumes of timber would enter the market (Munsell et al., 2009), or focused on goals to increase these private holdings (Hoyt and Hodges, 2010).

Types of Forest Owners

Forest land ownership in the United States falls into two broad categories, public and private, and each has a different propensity for harvesting timber (Barlow et al., 1998; Buongiorno et al., 1988; Jamnick and Beckett, 1988; Stone, 1970). Ownership broken into these two categories is a highly significant variable for modeling harvests (Young and Reichenbach, 1987). This is due to the dichotomy between public lands, primarily less managed with a more diverse species composition, and private lands, managed to some extent with the possible expectation of sale or lived on and used for materials (Berck, 1979; Beuter, 1976; Butler, 2005; Stone, 1970). With these differences in motivation for harvest and management, fewer harvests tend occur on public lands (Barlow et al., 1998; Greene and Blatner, 1986).

Economically, public lands tend to undergo harvesting for different reasons than private lands. Private lands frequently have single-owner decision makers and thus tend to be more liquid; they undergo harvests when prices are higher (Buongiorno et al., 1988; Max and Lehman, 1988). Overall, however, public stands, though harvested less frequently, are harvested with less stochasticity than private lands (Beuter, 1976; Birch, 1996; Jamnick and Beckett, 1988; Stone, 1970), likely due to the higher proportion of public owners having management plans (Joshi, 2007).

Public

Public land in the northeastern United States generally consists of federal, state, and local government entities (Arbuckle et al., 1993). These entities tend to harvest less frequently, though there is no reason to suspect that it is not equally as well managed, if not more so, than private forest (Barlow et al., 1998). Because of a reduced amount of harvesting, with less of a focus on financial objectives, public forests tend to have older stands and a more diverse species composition (Berck, 1979; Beuter, 1976; Johnson and Scheurman, 1977). Other research has found that stands in their natural state are more resistant to invasive species (Holmes et al., 2009;

Hu et al., 2009). Thus, it could be that the risk of invasive impact is reduced in these public stands, and as a result, the probability of harvest due to invasive species is also reduced. Harvests from national forests tend to be treated as fixed and insensitive to price in the long term (Adams et al., 1991). In the short term, however, Adams et al. (1991) argue that national forest harvesting increases in times of increased price.

Private

Public forests are generally more homogeneous than private forests with respect to the objectives and actions of their owners. Work by Barlow et al. (1998), Birch (1994), Buongiorno et al. (1988), Hoyt and Hodges (2009), Jamnick and Beckett (1988), Larsen and Gansner (1972), and Max and Lehman (1988)) tended to show that private owners' objectives are much more variable. Considering the different motivations of these varying owners, private lands can be split between two general groups: 1) those who have an active willingness to harvest, and 2) those who do not (Favada et al., 2009; Young and Reichenbach, 1987). Private ownerships can also be categorized roughly into industry, which is typically management and harvest oriented (Berck, 1979; Straka et al., 1984) and non-industrial private forest owners (NIPFs). NIPFs consist generally of two groups of owners, with differing proclivity to harvest (Birch, 1996; Favada et al., 2009; Gan and Kebede, 2005; Hoyt and Hodges, 2010; Joshi, 2007; Lönnstedt, 1997; Majumdar et al., 2008; Stone, 1970).

Among private forest owners, a previous harvest is strongly correlated with the likelihood of a future harvest (Hoyt and Hodges, 2010), and owners of large tracts "tend to harvest 2 to 1 over small and medium owners" (Larsen and Gansner, 1972). Having a management plan in place is also one of the strongest predictors of a future harvest occurring (Greene and Blatner, 1986; Larsen and Gansner, 1973; Young and Reichenbach, 1987) Most owners tend not to have a management plan (Birch, 1996; Joshi, 2007), though a great deal of work has been done on reaching owners who already support harvesting and offering to help manage their stands, which has been proven to increase landowner productivity (Larsen and Gansner, 1973).

NIPFs

Non-industrial private forest owners (NIPFs) make up roughly 60% of privately held forestland in the northeastern United States (Kittredge et al., 2003). Within this group, a distinction can be drawn between owners who align more closely with the harvesting patterns of industrial owners and those who have less predictable harvest behavior due to a number of factors (Birch, 1996; Bliss and Martin, 1989; Favada et al., 2009; Gan and Kebede, 2005; Joshi and Arano, 2009a; Lönnstedt, 1997; Majumdar et al., 2008; Max and Lehman, 1988; Munsell et al., 2009; Stone, 1970). These factors make it useful to divide private forest landowners primarily based on their original goals in owning land (Joshi and Mehmood, 2011).

Young and Reichenbach (1987) divided NIPFs into two groups. The first has a much greater propensity for harvest. This group tends to include highly educated individuals (Dennis, 1989; Greene and Blatner, 1986). They overwhelmingly tend to own larger tracts of forest land (Binkley, 1981; Bliss and Grassl, 1987; Gan and Kebede, 2005; Greene and Blatner, 1986; Hoyt and Hodges, 2010; Jamnick and Beckett, 1988; Larsen and Gansner, 1973; Lönnstedt, 1997; Reams and McCollum, 1999; Salkie et al., 1995; Sterba et al., 2000; Straka et al., 1984). They also tend to live away from the land they harvest, though not great distances from it (Butler, 2005; Carpenter, 1985; Sun et al., 2008). Frequently, they have consulted with a forester about selling timber from their property, or they have a management plan in place for their land (Gan and Kebede, 2005; Gong, 1998; Greene and Blatner, 1986; Hoyt and Hodges, 2010; Larsen and Gansner, 1973; Sun et al., 2008).

The second group has a reduced but volatile probability of harvest, and they make up the majority of NIPF private landowners (Stone, 1970). They tend to be landowners with homes on their forest land (Butler, 2005). They overwhelmingly prioritize recreation or aesthetics as one of the main factors for owning their land (Favada et al., 2009; Kuuluvainen et al., 1996; Majumdar et al., 2008; Pukkala et al., 2003). They tend to be younger than their harvesting counterparts (Butler, 2005; Gan and Kebede, 2005; Kuuluvainen et al., 1996). They also less likely to be in the farming profession (Binkley, 1981; Greene and Blatner, 1986; Hoyt and Hodges, 2010; Larsen and Gansner, 1973). In reality, though, this group’s lack of predictability of harvest means that other, less obvious factors contribute when a harvest does actually occur (Max and Lehman, 1988, p. 72). The need for money, for instance, was a reason frequently cited for harvesting (Carpenter, 1985; Kingsley and Birch, 1977; Young and Reichenbach, 1987).

Modeling and Variables

Types of Models

Approaches for analyzing timber harvests have taken on two primary forms in the literature, optimization and statistics. Researchers such as Nautiyal and Pearse (1967), Navon (1971), and Johnson and Scheurman (1977) focused on volume of timber harvested. This work was followed up by Tedder et al. (1980), Hof and Joyce (1993), Gustafson et al. (2006), and others. These groups applied Markov chains, linear programming, stochastic optimization models, and Monte Carlo designs to prescribe optimum harvest volumes and management activities. These models assisted project planners and landowners in determining how best to manage resources.

The second modeling approach uses statistical models to assess the significance of multiple factors to model or predict the probability that a stand will undergo a harvest given its specific characteristics. This is the focus of the research reported here. This approach was first employed by Binkley (1981) who utilized logistic regression combined with site and landowner attributes to model harvest probability. Binkley's work was followed by Bliss and Grassl (1987), Rucker and Leffler (1988), Reams and McCollum (1999), and Butler (2005). Jamnick and Beckett (1988) argued that the logit model was specifically warranted when considering multiple variables with the intention of predicting a harvest. This was further supported by Kingsley et al. (1977) and Schuster et al. (1983) who said that using more factors to explain the motivation behind harvest should be considered over simple models with only a few variables.

This work signaled a fundamental change in the direction of research at the time. Work was still being done, and is still being done today, on tools to help owners optimize forest management decisions, but the focus of this new area of research was to determine how likely harvests were to occur, given the wealth of ownership information coming out at the time. Munsell et al. (2009) called this a "Fundamental Shift," which marked the turning point from maximization-focused modeling, to a multi-objective approach that focused more on environmentalism. In more recent research, the focus has turned from general continuous variable only models, to specific logistic models that more frequently utilize categorical variables. Majumdar et al. (2008) outlined three groups of models, multiple-objective, non-timber, and timber. Favada et al. (2009) also identified ownership objective as an important categorical factor through principal components analysis. Sterba et al. (2000) devised specific models that focused on the type of harvest occurring, which were defined as harvest, thinning, or salvage, previously suggested for classification by Reams and McCollum (1999). This breakdown makes sense, given that "even owners who are averse to harvesting have an interest in thinning as a stand improvement" (Carpenter, 1985).

Independent Variables

Reassessing what factors influence the probability of harvest is important given that landowner preferences change over time (Carpenter, 1985), and also due to the diversity of NIPFs (Joshi and Arano, 2009b). Additionally, while a large amount of research has been done using questionnaires on why NIPF land owners choose to harvest, less has been done on other non-social factors such as market conditions, environmental factors, stand attributes, or potential threats such as impending invasive insect or disease damage (Kittredge et al., 2003).

Stand Characteristics

Geography

Lockwood and Moore (1993) suggested that terrain may be significant. Barlow et al. (1998) tested slope in Alabama and Mississippi and found that it was not significantly related to harvest probability. Later research by Sterba et al. (2000) and Butler (2005) found that elevation was significant to removal amounts and that increased slope significantly reduced harvest probability.

Even though smaller regions were expected to dramatically improve the models, state level variables worked almost as well, and were significant predictors of harvest (Schuster and Niccolucci, 1983). Reams and McCollum (1999) utilized region for modeling and determined that it was significant in modeling harvests.

Age Class and Timber Maturity

Categorical classification by age class was found to be a significant predictor of harvest probability, with increasing stand age being positively correlated with harvest probability (Butler, 2005; Johnson and Scheurman, 1977). Maturity of timber was a significant predictor of whether owners would harvest, with mature stands being one of the most important reasons cited by landowners as the reason for harvest (Carpenter, 1985; Kingsley and Birch, 1977; Young and Reichenbach, 1987).

Stand Volume, Size, Density, and Stocking Status

Per-acre volume was a significant predictor of harvest probability (Barlow et al., 1998; Butler, 2005; Dennis, 1989; Lönnstedt, 1997; Prestemon and Wear, 2000; Reams and McCollum, 1999), as was basal area (Butler, 2005; Sterba et al., 2000). Overall expectation was that increased volume would lead to increased harvest probability, given that harvests seek to maximize yield, though Butler (2005) found that higher volumes and basal area in hardwood stands correlated with a decrease in harvest probability. Reams and McCollum (1999) found that trees per acre was a significant predictor of harvest, and that a harvest probability increase corresponded to more softwood, and less hardwood trees per acre.

Canham et al. (2012) modeled trees in the northeastern United States and determined that diameter increased the probability of harvest. Reams and McCollum (1999) cited average pine stand diameter significantly positively correlating with increased harvest probability. Butler (2005) found that categorical stocking status was a significant predictor of the probability of harvest, with percentage of full stocking increasing the probability of harvest.

Distance to Road, Mill, and Urbanized Area

Lockwood and Moore (1993) and Reams and McCollum (1999) both suggested that road access may be significant. Then, Barlow et al. (1998) determined that proximity to an improved road significantly increased the probability of harvest. Distance to mill was thought to be significant by Reams and McCollum (1999), but was not tested in their study, without justification. Barlow et al. (1998) found that closer distances to urbanized areas significantly reduced the probability of being harvested. Reams and McCollum (1999) suggested that future research should be done on distance to urban populations. Butler (2005) found that increased housing density decreased the probability of harvest.

Forest Type and Stand Origin

Reams and McCollum (1999) found species mix to be a significant predictor of harvest, with increased pine significantly increasing the probability of harvest (Canham et al., 2012). Butler (2005) and Sterba et al. (2000) found proportion of conifers had an increasing effect on harvest probability. Butler (2005) and Reams and McCollum (1999) considered stand origin of natural versus artificial as a possible significant predictor of harvest. Butler (2005) found that in the southeastern US there was no significant effect.

Economic

National Economics and Taxes

The regional unemployment rate significantly correlated with an increased probability of harvest (Schuster and Niccolucci, 1983), and Birch (1994) suggested that the strength of the American dollar may be important. Buongiorno et al. (1988) found that "Local private harvests were not by influenced by housing starts or price."

Changes in future tax rates cause uncertainty, and thus have an effect on increasing the probability of harvest (Beuter, 1976), though Max and Lehman (1988) said that the increased harvests only occur for a short time after implementation of the tax.

Price

Real price received, corresponding to an increased probability of harvest, was the best predictor used by Schuster et al. (1983) and real price was found to be a significantly better predictor than nominal price. Adams et al. (1991) and Gong et al. (2005) utilized price as a variable in their models, though Provencher (1995) argued it should not be the only variable. Butler (2005) and Prestemon and Wear (2000) also said that stumpage price has a strong influence on the probability of harvest, but it is current market price rather than future price that significantly impacts harvesting (Lönnstedt, 1997).

Rucker and Leffler (1988) stated that "changes in initial stumpage values do not significantly affect harvest probabilities," and Adams et al. (1991) said that harvest schedules are largely independent of price. Plantinga (1998) said that harvest scheduling should be based on price. Reductions in price variability also caused an increase in harvest probability (Rucker and Leffler, 1988), and Gong et al. (2005) found that price uncertainty affects management decisions.

Landowner Characteristics

Income

Increasing income decreases the probability of harvest (Binkley, 1981), but owners in better financial positions have a stronger incentive to manage land (Straka et al., 1984). Landowner income was not a significant factor in whether a harvest would occur in a study by Larsen and Gansner (1973), but Binkley (1981), Jamnick and Beckett (1988), and Dennis (1989; 1990) showed that people were significantly less likely to harvest as income increased. On the other hand, Joshi and Arano (2009) found that income was positively correlated with the probability of management activity. Kuuluvainen et al. (1996) found a negative correlation between income and probability of harvest for single-objective owners, but found a positive correlation for multi-objective owners.

Age, Education, and Occupation

Older owners have a higher probability of harvesting than younger owners according to Butler (2005), Gan and Kebede (2005), and Kuuluvainen et al. (1996). However, Joshi and Arano's (2009) found that younger landowners had a higher probability of harvest.

Years of education was found to be significant to harvest, and education correlated with lot size in some areas (Greene and Blatner, 1986; Joshi and Arano, 2009b). Dennis (1989) said that years of formal education and harvest probability were significantly negatively related, suggesting that more educated landowners procured land for future recreational use.

Farmers are generally more likely to harvest (Binkley, 1981; Greene and Blatner, 1986; Jamnick and Beckett, 1988; Larsen and Gansner, 1973; Salkie et al. 1995). Occupation plays a role in probability of harvest (Gan and Kebede, 2005; Joshi and Arano, 2009b), and forest associated with agricultural land is significantly more likely to be harvested (Bliss and Grassl, 1987).

Land Holding Size and Residency

Total tract/land holding size has been shown to have a positive effect on the probability and volume of harvest, arguably more frequently than any other predictive variable (Binkley, 1981; Bliss and Grassl, 1987; Gan and Kebede, 2005; Greene and Blatner, 1986; Jamnick and Beckett, 1988; Joshi and Arano, 2009b; Kingsley and Birch, 1977; Larsen and Gansner, 1973, 1972; Lönnstedt, 1997; Salkie et al., 1995; Straka et al., 1984). Past harvest is also strongly correlated with an increased probability of future harvest (Larsen and Gansner, 1973).

Resident owners have been found to be less likely to harvest timber than non-residents (Butler, 2005; Carpenter, 1985; Jamnick and Beckett, 1988; Joshi and Arano, 2009b).

Management Plans

The implementation of forest management plans has been shown to significantly increase the probability of harvest (Gan and Kebede, 2005; Greene and Blatner, 1986; Hoyt and Hodges, 2010; Jamnick and Beckett, 1988; Joshi and Arano, 2009b; Larsen and Gansner, 1973). The probability of harvest also increases if the landowner has had contact with a state forester (Bliss and Grassl, 1987; Greene and Blatner, 1986).

Chapter 3 - Methods

Modeling work began following the general examination of the available literature on various approaches to modeling harvest regimes, as described in the previous chapter. The study region was selected based on research previously conducted by The Pennsylvania State University APHIS project research team, in conjunction with Dr. Canham of the Cary Institute. They selected the 22-state region encompassing the northeastern United States, which also shows the spatial distribution of FIA plots within the region, by the eight broad forest types used by Canham. This 22-state region contains approximately 465,102,080 total acres, of which roughly 46% of the area is forest (Worldbank.org, 2016).

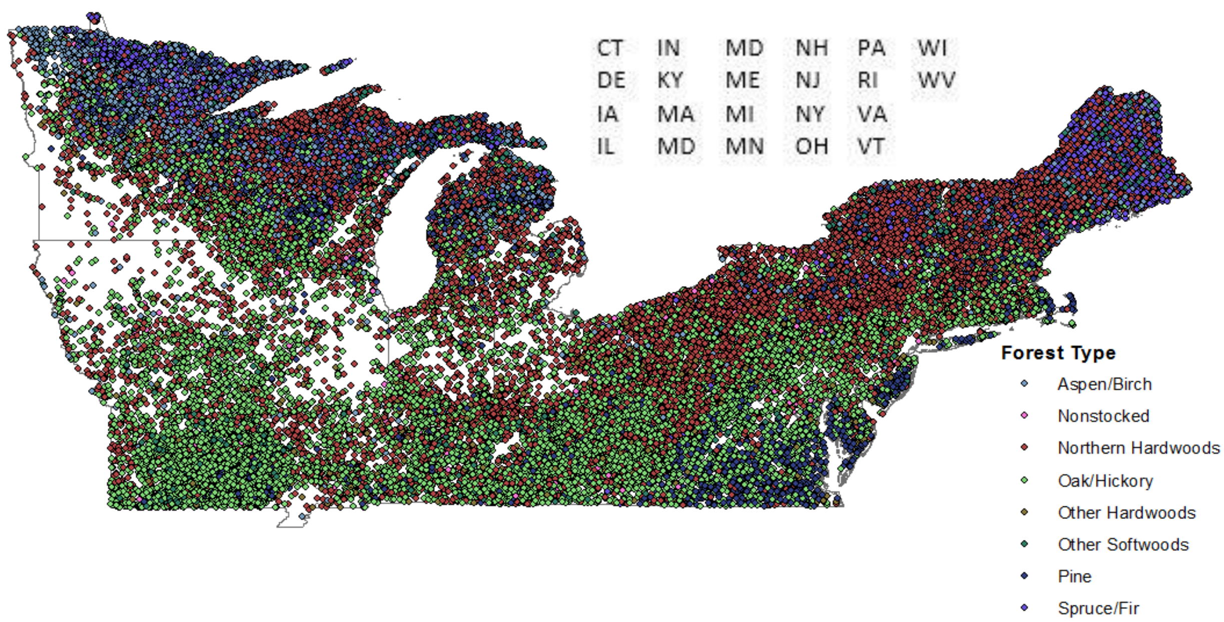

Figure 1 - FIA Plot Distribution within the study area by Forest Type based on Dr. Canham Forest Type

The primary data used to create these models is derived from the US Forest Service's Forest Inventory Analysis (FIA) program. This is a continuous plot survey system that samples 1/6-acre plots that are randomly distributed within hexagons in a grid overlaid over each state in the United States. Sites are sampled remotely for forested/non-forested status by the US Forest Service, and forested plots are then sampled on the ground by crews, roughly on a five-year interval. This allows for the observation and quantification of site metrics dealing with all aspects of vegetative growth on the plot (volume, size, condition), as well as a variety of site-specific factors (location, elevation, ownership, etc.). Because plots are randomly distributed, it is possible for a plot to fall on multiple conditions, based on forest type and ownership. It is imperative that when a plot represents multiple conditions, the corresponding areas are defined separately. The FIA uses the concept of "condition" to accomplish this. A "plot-condition" therefore represents a subset of a plot – in most cases, the entire plot – that all belongs to the same condition, i.e., shares the same forest type and ownership characteristics. When separate plot conditions occur on a plot, the condition-proportion field gives the percentage of the plot represented by that particular condition. Plot measurements are mapped to the condition on which each item was located so that data can be associated with the appropriate plot-condition.

In this study, a plot-condition was considered an observation, and plot-conditions that did not represent at least a half of a plot were dropped. Thus, the effect of the plot-condition is that some plots are less than 1/6th acre and some plots were dropped completely – if there were more than two plot-conditions and none of the plot-condition proportions were greater than a half. To then make volumetric assumptions across remaining plots, the expansion factors of plots with a plot-condition proportion less than 100% were normalized by dividing them by the plot condition proportion.

Preliminary examination of general FIA plot attributes for the study area showed diverse forest types, with mostly northern hardwoods and oak-hickory in the southern part of the study area, and aspen-birch and spruce-fir in the northern part, as shown in Figure 1.

Since the goal of this research was to predict and explain harvesting behavior, preliminary model exploration focused on specific forest type regions within the area. Those areas can be broken down by observed boundaries, such as state lines or groups of states, or ecological boundaries, such as forest or species type (Canham et al., 2012).

Defining a Harvest

As mentioned above, FIA is a continuous sampling system of permanent plots across the United States. Vegetation on a given plot was measured and recorded every five years in most states, except in Virginia and Kentucky where plots were re-measured every six and four years, respectively. This four-to-six-year period is called the measurement cycle, and all plots within a state were measured at some point within this cycle, unless they were excluded from the study for an unforeseen reason. The initial four-to-six-year measurement period, which will be referred to as cycle 1, varied for each state, as the FIA continuous inventory program began in different years in different states. Plots were then re-measured over a second four-to-six-year cycle. Data from this second cycle, cycle 2, were used in this research to determine whether a harvest had occurred on a plot and, if so, which trees were harvested. A list of the data sets used for each state can be found in Table A1.

The definition of harvest in this research is that at least one single tree on the plot was removed by human activity between cycle 1 and cycle 2. This was determined using the FIA tree status code from cycle 2. For each plot, the trees present and alive in cycle 1 were identified, and a tree list for each plot was populated. Tree status code was used to include only trees that were living in cycle 1. This tree list was used to calculate various plot-level attributes, such as per-acre volume, basal area, and average tree diameter. Knowing that a tree (or stump) can be tracked between cycles is the foundation for determining if it remained or was removed, and it allows the plot to be marked as harvested. This plot harvest status is then used to select only trees on plots that underwent a harvest, for the tree models. The plot and tree classification scheme used to produce the datasets can be seen in Figure 2.

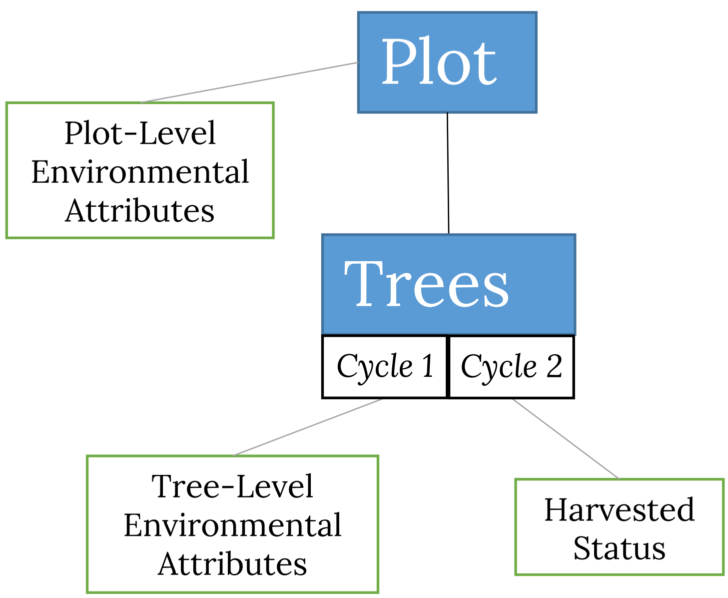

Figure 2 – Harvest grouping methodology showing both plot and tree model steps.

Modeling Outline and Workflow

One goal of the regression models developed for this research is to simulate harvests on FIA plots. One set of multinomial logistic models can be used to predict the probability of three different types of timber harvests. The three types of harvests are: 1) low-intensity thinnings (<20% of the basal area (BA) removed, e.g., firewood harvesting), 2) moderate-heavy thinnings (between 20% and 85% of the BA removed, e.g., selection harvests, diameter-limit harvests, or shelterwood harvests) and 3) stand-replacing harvests (>85% of the BA removed, e.g., clearcuts, overstory removals, seed-tree harvests). These harvest intensity categories were chosen because it was hypothesized that the motivations differed for different types of harvests and, as a result, different variables would impact different types of harvests in different ways. Since preliminary analyses found that nearly all harvests remove only some of the trees, a second set of logistic regression models was also developed to predict which trees on the plot will be harvested, or, more precisely, whether a given tree on a plot that has been selected to be harvested will be harvested. Thus, there are two prediction steps in using these models. The first determines whether or not a plot will be harvested, and, if so, what type of harvest will occur. The second determines whether a specific tree on that plot will be harvested, given the type of harvest and other factors.

Plot Models

The plot models developed here give a probability of whether a given plot will undergo a harvest, and if so, what categorical type of harvest. For this stage, separate multinomial logistic regression models were developed for five broad stand-origin/forest-type combinations: 1) Artificial stands (any planted stand, but most are softwoods), 2) Natural Aspen-Birch stands, 3) Natural Northern Hardwood stands, 4) Natural Oak-Hickory stands, and 5) Natural Softwood stands. These groups are aggregations of more detailed forest types (Table 1) and are referred to as “plot modeling categories” below. For each of these plot modeling categories, a multinomial probability model was fit with four outcomes: 1) low-intensity thinnings (<20% of the BA removed), 2) moderate-high intensity thinnings (between 20% and 85% of the BA removed), 3) stand-replacing harvests (>85% of the BA removed), and 4) no harvest. Models corresponding to the first three outcomes give a probability of each type of harvest. These probabilities sum to less than one, with the remaining probability being the probability of no harvest. The independent variables in the models are latitude and longitude, ownership (public vs. private), average diameter and average diameter squared, basal area per acre (a density measure), net board foot volume per acre, net cubic foot volume per acre, value per square foot of basal area, slope, county population density, distance to a mill, distance to road, and some forest type sub-categories (for example, Oak-Hickory, Oak-Pine, Other Hardwoods, and Swamp Forests within the larger Natural Oak-Hickory Modeling type). Initial diagnostics of plot counts by basal area harvested informed decisions on utilizing different harvest outcome groupings. The overall distribution of plots harvested by basal area removed is shown in Figure 3.

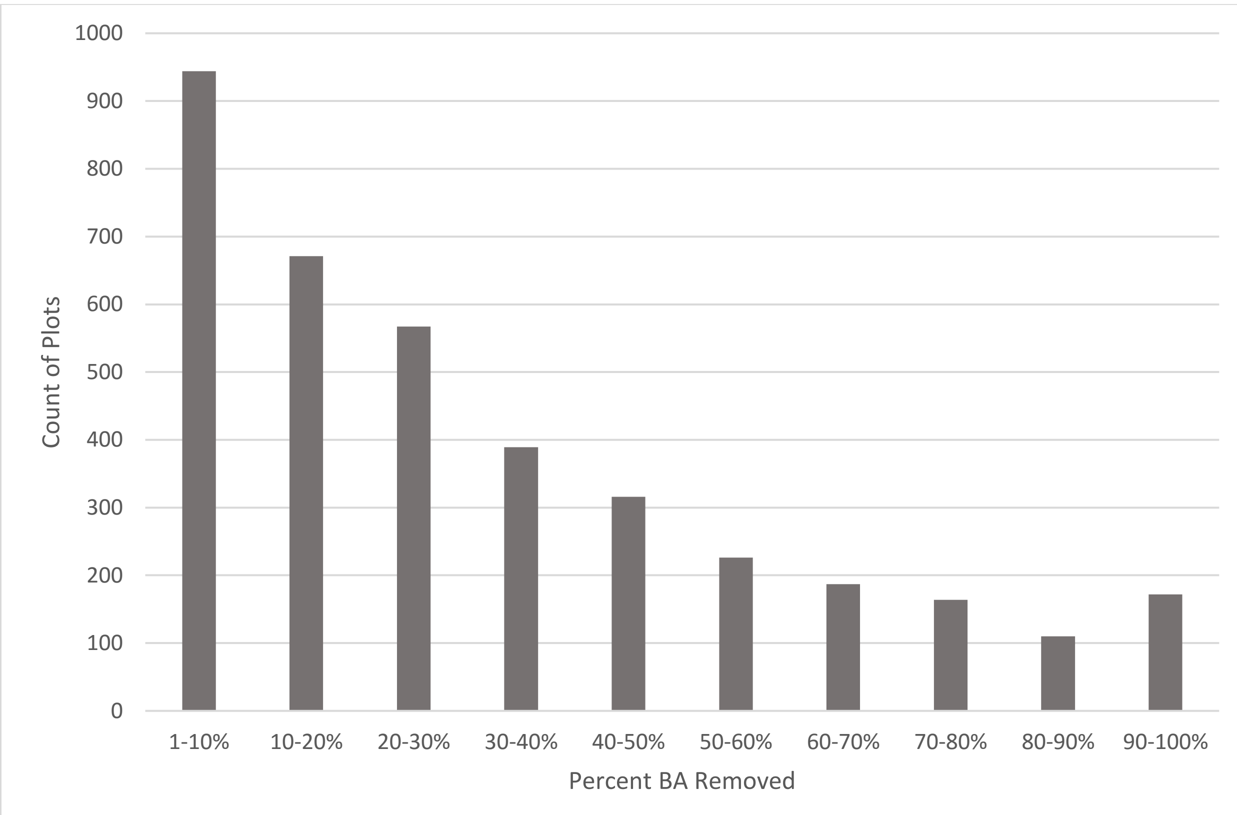

Figure 3 –Distribution of the harvested FIA plots by percent of basal area harvested.

Dividing the data

Initial modeling showed a clear difference between harvesting that occurred on plots that were artificially regenerated and those that were naturally regenerated. Forest type also varied greatly between the two groupings, with artificial plots having a softwood-to-hardwood ratio of roughly 2.5:1, versus 0.16:1 for natural stands. The literature also supports the assumption that harvesting motivation is different for plantations than for naturally-regenerated stands (e.g., Butler 2005). Based on this information, we chose to develop separate models for plantations and naturally-regenerated stands (Figure 4).

In addition to separating the data sets based on stand origin, we also chose to divide the data based on broad forest types that are aggregates of Canham forest types, shown in Figure 1. As the figure shows, these forest types also roughly correspond to regional species distributions. Because of the correlation between the broad forest type categories and region, no regional factor was ultimately included in the model, except latitude and longitude. In preliminary model testing, region was not a strong predictor when it was included with forest type, while forest type was significant. This suggested that regional variation in harvesting activity could better be accounted for, which was also used by Canham et al (2012). In some cases, it might be desirable to model specific categories of forest types, but lack of data made it impossible to accomplish this with separate data sets and separate models. To account for differences between these finer forest type groups, less aggregated forest type categories were also used as categorical variables in some of the models to capture some differences between harvesting behavior among forest types. This is discussed in greater detail below, when specific variables are described.

Figure 4 summarizes how the FIA data for the 22-state region were divided into separate data sets for modeling purposes. The data were first divided by regeneration type. There were not enough observations to further subdivide artificially-regenerated plots. Data from naturally-regenerated plots were then subdivided into softwood and hardwood forest types. The naturally-regenerated softwood data set was also too small to subdivide further. Finally, the naturally-regenerated hardwood plot data were subdivided into three broad forest-type groupings: 1) aspen-birch plots, 2) oak-hickory plots, and 3) northern hardwood plots. Table 4 (on p. 26) shows the total number of plots in each of these data sets and the number and percentage of plots that were harvested by harvest category. The relationship between the broad forest type categories used here and Canham forest types is shown in Table 1.

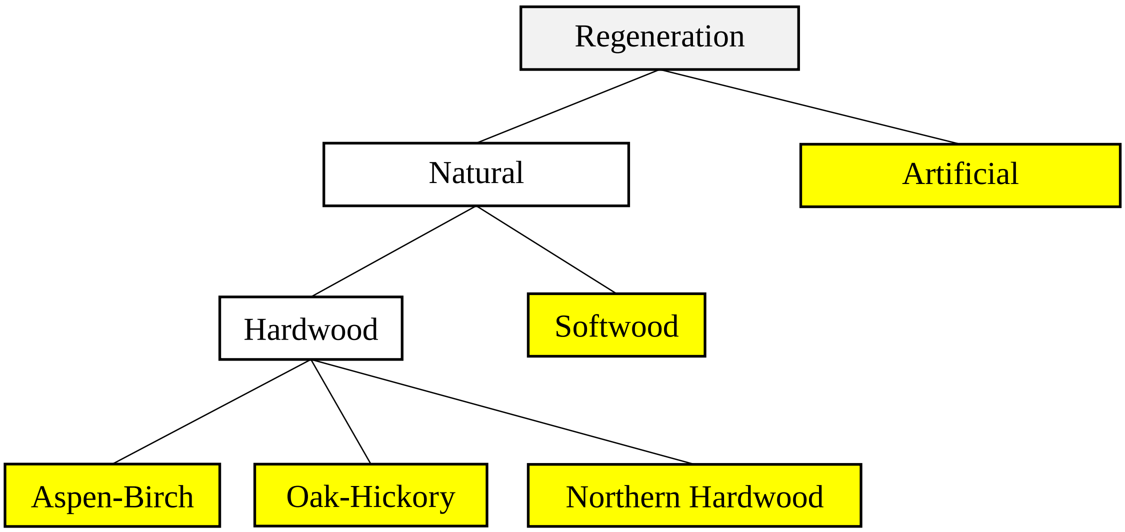

Figure 4 – Diagram illustrating the data partition followed to develop the plot level models. A model was fit for each group in the terminal boxes.

Table 1 **– Dr. Canham forest types with corresponding plot modeling categories used for this study.**

Canham Forest Types	Plot Modeling Category for *Natural* Stands
Aspen – Birch	Natural Hardwood (Aspen-Birch)
Northern Hardwood	Natural Hardwood (Northern Hardwood)
Oak – Hickory	Natural Hardwood (Oak-Hickory)
Oak – Pine	Natural Hardwood (Oak-Hickory)
Other Hardwoods	Natural Hardwood (Oak-Hickory)
Swamp Forests	Natural Hardwood (Oak-Hickory)
Northern Pines - Hemlock	Natural Softwood
Southern Pines - Other Conifers	Natural Softwood
Spruce – Fir	Natural Softwood

Tree Models

The FIA tree data for the harvested plots in the 22-state region were divided into 30 separate data sets for fitting models to predict the probability of an individual tree being harvested. Tree data from plots that were not harvested were not used for this part of the work. Division of the data was based on five different plot-level stand types (artificial, natural aspen-birch, natural oak-hickory, natural northern hardwoods, and natural softwoods,) three possible harvest types based on the plot level harvest (less than 20% BA removed, between 20% and 85%

BA removed, above 85% BA removed,) and is further subdivided by ownership class (public/private). Tree record counts by stand origin, forest type and harvest categories are shown in Table 2. Model methodology was similar for tree models and plot models except that the tree models are binomial logistic models while plot models are multinomial logistic models. Variables differed between models, although some plot-level variables were based on tree level data (e.g., average tree diameter). Owner was the common variable used in both model sets. Separate logistic regression models were fit for each of these 30 tree-level data sets.

Table 2 - Tree record counts and proportions by stand origin, forest type and harvest category.

	Above 85%		Between 20% and 85%		Less Than 20%		**Grand Total**
Stand Origin/Forest Type	No Harvest	Harvest	No Harvest	Harvest	No Harvest	Harvest	
Artificial							
Hardwoods	6 (6%)	93 (94%)	257 (57%)	191 (43%)	560 (91%)	55 (9%)	1162
Northern Pines	101 (14%)	633 (86%)	2277 (60%)	1522 (40%)	1622 (85%)	294 (15%)	6449
Southern Pines	102 (12%)	759 (88%)	1995 (52%)	1835 (48%)	408 (89%)	50 (11%)	5149
Natural Hardwood							
Aspen - Birch	464 (21%)	1738 (79%)	4644 (58%)	3417 (42%)	4156 (92%)	348 (8%)	14767
Northern Hardwood	152 (17%)	747 (83%)	14876 (68%)	7162 (32%)	17187 (92%)	1405 (8%)	41529
Oak - Hickory	117 (15%)	675 (85%)	11039 (71%)	4433 (29%)	17393 (94%)	1205 (6%)	34862
Oak - Pine	46 (15%)	265 (85%)	1530 (65%)	826 (35%)	1981 (91%)	190 (9%)	4838
Other Hardwoods							332
Swamp Forests	25 (17%)	120 (83%)	1109 (70%)	474 (30%)	2324 (94%)	146 (6%)	4198
Natural Softwood							
Northern Pines - Hemlock	166 (23%)	546 (77%)	2156 (60%)	1459 (40%)	3120 (93%)	242 (7%)	7689
Southern Pines - Other Conifers	28 (9%)	294 (91%)	738 (59%)	520 (41%)	363 (92%)	33 (8%)	1976
Spruce - Fir	129 (15%)	749 (85%)	4557 (61%)	2966 (39%)	3557 (91%)	354 (9%)	12312
Grand Total	1336 (17%)	6621 (83%)	45240 (65%)	24872 (35%)	52870 (92%)	4337 (8%)	135276

Defining Variables

Based on the variables identified in the literature review and the variables that are available in the FIA database, an initial variable list was created and expected relationship to harvest probability was outlined. The majority of the variables came from the FIA database, but data from external sources, including stumpage prices and census data, were also used.

FIA Data

The literature review suggested that several environmental factors could be useful for modeling harvest probability. Most environmental factors can be classified into two groups: 1) factors relating to the trees on the plot, or 2) factors relating to the environment of the plot.

Data organization initially started with the FIA database, using Microsoft Access queries. Whether a harvest occurred was determined by the status code of the tree in cycle 2, as outlined above in *Defining a Harvest*. This initial dataset was the starting point from which to add other variables to the dataset from both FIA data and secondary sources as well. All volume metrics (including basal area) are expanded at the tree level to per-acre values using the trees-per-acre FIA field. As tree data were gathered and processed, all trees per plot condition were summed to the plot level and expanded to a full plot volume estimate by dividing by the plot condition proportion, allowing for a uniform model assessment.

Plot Variables

Forest Type Groups

The FIA defines 207 specific forest types for the entire United States. Additionally, FIA also defines 34 forest type groupings. Within the study region, a total of 80 forest types was observed, which can be aggregated into 17 FIA forest type groups. To further reduce possible categories while still preserving key forest type differences, forest types in this list were further combined to arrive at a reduced list of nine forest types as defined to the working group by Dr. Canham ("Canham forest types" hereafter).

The broad stand-origin/forest-type categories that were used in this research to divide the data set (see Table 3), referred to here as plot modeling categories, are aggregates of some very different forest types. Lack of data forced us to combine these different forest types for modeling purposes, but there likely are substantial differences in the likelihood, and even in the variables that influence the likelihood of harvest, between these types. Thus, several models include a categorical forest type group variable to at least capture differences in the likelihood of harvest for different forest type groups within the broader modeling categories. Table 3 shows the set of forest type groups used for each plot modeling category where a forest type group variable was used and the relationship of the different levels of each forest type group to the Canham forest types.

Categorical variables require that one level be designated as the "reference level" for that variable, and the coefficients for the remaining levels indicate any difference between that level and the reference level. Reference levels for forest type groups were selected based on the group containing the largest number of observations. Thus, "Northern Pines" was the reference forest type group for the artificial models; "Oak-Hickory" was the reference level in the Natural Oak-Hickory models, and "Spruce-Fir" was the reference level in Natural Softwood models. Two models, Aspen-Birch and Northern Hardwoods, do not use forest type group as a variable since they contain only one forest type group.

Table 3 – Relationship between plot modeling categories, Canham forest types, and forest type groups. (Asterisks show reference levels for forest type groups.)

Plot Modeling Category	Canham Forest Type	Forest Type Group
Artificial	Aspen - Birch	Hardwoods
Artificial	Northern Hardwood	Hardwoods
Artificial	Northern Pines - Hemlock	Northern Pines*
Artificial	Oak - Hickory	Hardwoods
Artificial	Oak - Pine	Hardwoods
Artificial	Other Hardwoods	Hardwoods
Artificial	Southern Pines - Other Conifers	Southern Pines
Artificial	Spruce - Fir	Northern Pines*
Artificial	Swamp Forests	Hardwoods
Natural Aspen – Birch	Aspen - Birch	No forest type groups
Natural Northern Hardwood	Northern Hardwood	No forest type groups
Natural Oak – Hickory	Oak - Hickory	Oak – Hickory*
Natural Oak – Hickory	Oak - Pine	Oak – Pine
Natural Oak – Hickory	Other Hardwoods	Other Hardwoods - Swamp Forests
Natural Softwood	Northern Pines - Hemlock	Northern Pines - Hemlock
Natural Softwood	Southern Pines - Other Conifers	Southern Pines - Other Conifers
Natural Softwood	Spruce - Fir	Spruce – Fir*

The division of data into plot modeling categories and forest type groups was done so that each harvest category and forest type group would contain a minimum number of observations, as indicated in Table 4.

Table 4 - Plot counts by plot modeling category, forest type group and harvest type, bold totals are for separate models.

	>85%	20% to 85%	<20%	No Harvest	Total
Artificial - Hardwoods	3 (<1%)	18 (4%)	17 (3%)	448 (92%)	486
Artificial - Northern Pines	16 (2%)	74 (10%)	48 (6%)	614 (82%)	752
Artificial - Southern Pines	15 (3%)	69 (15%)	9 (2%)	365 (80%)	458
Total Artificial	**34 (2%)**	**161 (9%)**	**74 (4%)**	**1,427 (84%)**	**1,696**
Total Natural Aspen – Birch	**63 (1%)**	**204 (5%)**	**112 (3%)**	**4,024 (91%)**	**4,403**
Total Natural Northern Hardwood	**26 (<1%)**	**591 (7%)**	**498 (6%)**	**6,896 (86%)**	**8,011**
Natural Oak-Hickory – Oak-Hickory	31 (<1%)	556 (4%)	626 (4%)	13,194 (92%)	14,407
Natural Oak-Hickory – Oak-Pine	10 (1%)	73 (5%)	58 (4%)	1,195 (89%)	1,336
Natural Oak-Hickory – Oth. Hdwds - Swmp For.	6 (<1%)	59 (2%)	79 (3%)	3,009 (95%)	3,153
Total Natural Oak-Hickory	**47 (<1%)**	**688 (4%)**	**763 (4%)**	**17,398 (92%)**	**18,896**
Natural Softwoods – No. Pines - Hemlock	20 (2%)	90 (8%)	83 (7%)	993 (84%)	1,186
Natural Softwoods – So. Pines – Oth. Conif.	8 (1%)	35 (6%)	10 (2%)	543 (91%)	596
Natural Softwoods – Spruce - Fir	18 (1%)	145 (4%)	74 (2%)	3,061 (93%)	3,298
Total Natural Softwoods	**46** (1%)	**270** (5%)	**167** (3%)	**4,597** (90%)	**5,080**

Average Diameter and Average Diameter Squared

The average diameter (in inches) of all trees on the plot is a measure of stand maturity. The expectation is that plots with larger trees will be more likely to be harvested, as larger trees have greater volume and generally slower growth rates (as a percent of volume). Tree size has been suggested in the literature to be a predictor of harvesting activity (Butler and Leatherberry, 2004; Canham et al., 2012). This should equate to a higher probability of harvest in tree models as well. Based on these results, the square of the average diameter was also included.

Basal Area

The basal area (BA) per acre is calculated from the diameter of the trees on the plot using the following formula 1, where the sum is over the trees in the plot tree list.

$$BA = \sum_{i=1}^{n}((dbh_i^2 * 0.05454) * Trees\ per\ Acre\ Expansion) \qquad \text{(Equation 1)}$$

where:

BA is the plot basal area in ft^2/acre

dbh is the diameter at breast height of the i^{th} tree in inches

i is a tree index

n = number of trees a the plot

Stands with more BA are denser and more likely to benefit from thinning and also tend to have greater value. Basal area per acre is assumed to be positively related to the likelihood of a harvest. The units of basal area are $feet^2$ per acre; this variable was divided by 100 to normalize coefficients.

Wood Volume in Board Feet

At the plot level, this is the sum of the net board foot volume of trees, on a per-acre basis. Board foot volume indicates the amount of lumber that can be sawn from a tree. Cull (unusable) volume has been removed from net board foot volumes. Wood that can be used for sawtimber typically fetches a much higher market value than wood that can only be used for pulpwood or fuelwood. Trees must reach a minimum diameter (e.g., 12 inches for hardwoods) before they contain any board foot volume. Merchantable timber volume should be positively related to the probability of harvest. It is reported in board feet, and was divided by 1000 to normalize model coefficients.

Wood Volume in Cubic Feet

The sum of cubic-foot volume of trees, per acre. Cubic feet is included because it encompasses all of the volume of the tree bole, from the crown and stump, instead of simply merchantable board feet volume. This variable is a more accurate representation of the volume that can be harvested for pulpwood or fuelwood.

Tree Models

Wood Volume in Board Feet

Tree models utilize total net board foot volume per tree. Higher board foot volume trees should be more valuable, and therefore more likely to be harvested.

Wood Volume in Cubic Feet

Tree models use total net cubic foot volume per tree. Higher cubic foot volume should be more valuable desirable, and therefore have an increased likelihood of being harvested.

Cull

The percentage of volume in a live or dead tree that is rotten or otherwise unusable. Approximately 51% of total trees sampled had some amount of cull on them, with an average of 3.5% overall. Trees with a high percentage of dead material may be less desirable for a harvest. The expectation is that as the percent dead material increases, the probability of harvest will decrease, though it could also increase if the harvesting objective is to improve the stand.

Diameter and Diameter Squared

The tree models include diameter of the tree measured in inches at breast height (DBH). Diameter is reported for any tree above 1" DBH. The expectation is that larger diameter trees contain more volume and have a lower percentage rate of growth and are therefore more likely to be harvested. Expecting that average diameter would behave similarly in the tree models as in the plot models, the squared tree diameter was also included.

Species

Tree species is a categorical variable that is potentially important for modeling harvests at the tree level. Unique species per state were also used to link the FIA data to the stumpage price data as discussed below. For plots in the 22-state region, there are 146 unique tree species from the FIA species list. Because of the large number of species, and the desire to model species categorically, it was necessary to aggregate these species into a manageable number of species groups to create a useable categorical variable for the tree-level models.

Species were aggregated into groups for two purposes. First, pricing data were obtained from a variety of states, each with its own methodology for combining their state's species into price groups. Therefore, a lookup table had to be constructed for each state to map tree species to species price categories using that state's methodology (Table A2). Similarly, for modeling purposes, as stated above, a lookup table was used to aggregate all FIA species within the study area to a reduced modeling species group list, outlined in Table A3. Commonality between species and price groupings used by timber market price reports from a variety of states informed the species groupings used in predictive species group categories. Table 5 lists the set of modeling species groups that was used. The reference species for each species group variable is the species group with the most observations in that modeling category (forest type/origin combinations). Reference species for each modeling category are also shown in Table 5.

Tree species potentially covers multiple effects in this model. Specifically, one might hypothesize that harvesters target higher quality/value species. Alternatively, landowners interested in improving their timber stands might target lower quality/value species for removal.

Table 5 – List of all species groups used in the tree models, with included reference category for each plot model. Species groups that serve as the reference species for a given modeling category are indicated, with the corresponding modeling category.

Harvest Species Group Name	
American beech	Other valuable hardwood
Ash	Other white oak
Aspen (Ref - AB)	Red and white pine (Ref – Art)
Birch	Red maple (Ref – OH)
Elm	Southern-jack pine
Hickories	Spruce-fir (Ref – Soft)
Miscellaneous hardwoods	Sugar maple (Ref – NH)
Non-canopy	Valuable red oak
Non-commercial	White oak
Other maple	Yellow-birch
Other red oak	Yellow-poplar
Other softwoods	

Timber Product Price Data

How price affects harvest activity is a topic that has not been explored much in previous statistical models of timber harvesting behavior. However, economic theory would suggest that price data might add considerably to making accurate predictions. Price data were gathered by soliciting prices from all states within the 22-state region. Some sources responded with specific datasets, and other datasets were compiled manually by acquiring data from websites. Although 22 states were used in the study, price data were only available for ten states. Several states do not actively track timber prices (see table A2), and in those instances, surrounding states with similar species were used to calculate prices. Price data were gathered for a 12-year period for all available states. Price data for available states were initially gathered by Zak Miller, a MS student under Michael Jacobson.

State Price Groupings

Data gathered from the ten states' timber market pricing reports varied greatly by species groupings and prices for particular species. This suggested a need to value species on a state-by-state basis instead of using one price for a species over the entire study area. These prices vary widely due to regional variation in markets and species quality, and they were combined to roughly follow FIA species groupings at a state level. For example, black oak could be in a mixed oak classification in Pennsylvania, while black oak in Delaware could have a unique black oak category. There were two important factors in the methodology behind these groupings: 1) different states' relative location to each other, and 2) similarity in the species distributions of these states.

Given that FIA plots are measured on four-to-six-year intervals, it is not possible to know exactly when a harvest occurred on a plot. All that is known is that at least one tree was harvested in between measurements. Thus, the average of the prices for the four or six year interval corresponding to cycle 1 was used to approximate the price for standing timber for each state *(see table A1 for cycle dates by state).*

Value Density (Value per Ft^2)

To capture the "value density" of a stand, we developed a metric by dividing the total value per acre of standing timber on a plot by the total basal area per acre. The expectation is that areas with higher values per ft^2 of basal area, in other words, a higher density of value, will be more likely to be harvested as each unit value requires less volume removed. The units of this variable are dollars per square foot. The variable was divided by 1000 to normalize the coefficients. Equation 2 outlines the method for calculating value per square foot.

$$Value\ Density = \frac{\sum((Board\ Foot\ Volume * Trees\ per\ Acre\ Exp) * Species\ Price)}{\sum(Basal\ Area * Trees\ per\ Acre\ Exp)} \qquad \text{(Equation 2)}$$

where:

Value Density is in dollars of board feet, divided by basal area per acre.

Board foot volume is net board feet of the plot.

Trees per Acre Exp. is the trees per acre expansion factor to bring volumes to a per acre metric.

Basal area is the plot basal area in ft^2/acre

Geolocational Data

Distance to Mill

Distance to mill was obtained using point locations of mills in the northeastern US, provided by a 2005 census done by the US Forest Service, and shown in Figure 5. The data were available in the form of an ArcGIS shapefile which was combined with a shapefile location of all plots in the primary sample dataset. A *nearest neighbor* query was then run on the datasets with the basis being the plot locations and the nearest neighbors being the mills. This query identified nearest distances to mills for each plot location, which was stored as a continuous variable measured in miles.

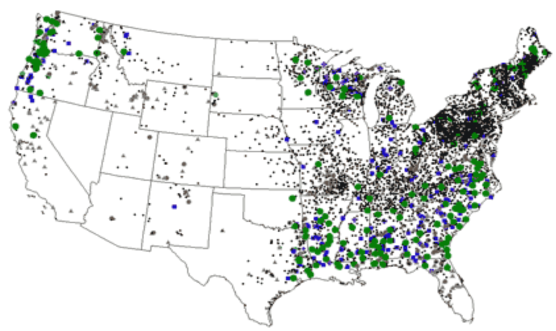

Figure 5 – Map of mill locations supplied by the US Forest Service for use in determining distance to mill.

The variable is listed in miles to the nearest lumber mill. This is linear distance and not based on a road network. The assumption is that plots closer to mills will be more likely to be harvested. This may be especially true in low basal area harvests, where harvesting activity may occur with less silvicultural planning, where access and operability factors may influence harvesting.

Ownership

The type of stand owner could play a large role in harvesting activity, as public entities may have different ownership objectives than private landowners. Two ownership class were defined: public and private (a table linking the classes to their constructed classes is seen below in Table 6), with each plot falling into one of those two ownership classes. Because market or financial goals are more likely to drive the decision making of private landowners, they may have a higher likelihood of harvesting plots relative to public landowners.

Table 6 - Owner group categories used to classify groups into public or private ownership.

OWNGRPCD	Description	Ownership Group
10	Forest Service (OWNCD 11,12,13).	Public
20	Other federal (OWNCD 21,22,23,24,25).	Public
30	State and local government (OWNCD 31,32,33)	Public
40	Private (OWNCD 41,42,43,44,45,46)	Private

Latitude/Longitude

Latitude and Longitude are the specific northing and easting of a plot, listed in decimal degrees. Because harvesting behavior may vary by plot location, this variable is intended to capture broad regional differences in harvesting behavior. This variable is fuzzed by up to a mile to protect the location and privacy of the plot and its landowner. All variables except for population density and distance to mill are in the FIA database, and thus are unaffected by this built-in error. For census and mill data, we assume that although plot location is not absolutely accurate, this slight variation will average out overall, and thus not affect the estimated variable response and significance.

Slope

The slope of the stand is also expected to influence the likelihood that a plot will be harvested. Stands on steeper slopes may be harder to access, harder to operate on, and more sensitive to harvesting activity and are therefore expected to be less likely to be harvested. The slope variable is reported as slope angle, in percent.

Distance to Road

The distance to the nearest improved road can influence the likelihood that a plot will be harvested. One would expect that more remote stands are less likely to be harvested.

Furthermore, basal area removed, corresponding roughly to firewood, thinning/shelterwood, or overstory removal cuts, may be affected by the distance to a road.

Distance to road is recorded in the FIA database as a categorical variable. It was converted to a continuous variable of distance in feet for use in the model using the midpoint distance for each category as shown in Table 7. For modeling purposes, the measurement of feet was converted to miles to be consistent with other distance measurement metrics. The rationale behind using a continuous variable was the data sparsity that arose from predefined categories. After combining groupings for a reduced subset, variable still caused too much sparsity given the hierarchical breakdown of forest type and harvest type into unique models.

Table 7 - Distance to road group categories showing distance in feet, which is converted to miles for use in the models.

Distance To Road	Group Distance To Road
100 feet or less	50
101 to 300 feet	200
301 to 500 feet	400
501 to 1000 feet	750
1001 to 1/2 mile	1320
1/2 to 1 mile	3960
1 to 3 miles	10560
3 to 5 miles	21120
Greater than 5 miles	36960

Census Data

Data from the US Census were also considered for possible use in the model. Census data include a variety of socio-economic variables, including county population, average family size, median income, male/female proportion, and median age. Plot points were used as the primary record, and merged with county data within the county boundaries they fell in. This data was then added to the plot record.

Census Density Data (Plot)

Population density is given by the population of the county divided by the land area in square miles in that county. These data were derived from the US census. Higher population densities could suggests a more urban setting, with a reduced likelihood of being harvested. This metric was then divided by 100 to normalize model coefficients.

Statistical Methods

After defining the variables to be used for modeling, statistical work could begin to estimate a relationship between harvesting and the predictor variables.

Model Selection

Many environmental plot-level attributes can be used to predict harvest activity. A methodological process was employed to select only variables that were significant in the model. The first step of this process was a stepwise model selection, using the full list of variables extracted from the FIA database. In this step, all variables with a p-value greater than 0.05 were removed from the model in a stepwise manner, using an automated script in R.

This initial model selection step resulted in a reduced variable list for both the plot and tree models. Given that models were created that covered different stand origin and forest type groupings, but that each model was to be reduced to the best possible model (as described under "Plot Models" below), the decision was made to employ a uniform selection criteria to all models to determine each of the final best models.

This best model final best model selection step reduced variables in the models based on a weighted combination of R^2, AIC, and BIC. Three variables were all similarly related to plot volume and were of interest in the final model selection step, though they may not have been significant in all basal area removed categories. For the plot models, these variables were board feet, cubic feet, and value per square foot of basal area. In the tree models, the variables of interest in this final selection step were board feet per acre and cubic feet per acre.

In this final reduction step for the tree models, the AIC, BIC, and McFadden R^2 for all possible combinations of the above variables for each model were weighted using the weights 0.4 for AIC, 0.2 for BIC, 0.4 for McFadden R^2, respectively. These weighted values were then summed to produce a metric which was manually interpreted to determine the best overall reduction in AIC and BIC, and the best R^2 statistic, and thus the best final model variable set in each forest type/stand origin category.

Logistic Regression

Logistic regression was the primary regression method used for both the plot models and tree models. The plot models used multinomial logistic regression, which allows multiple possible outcomes. The result of a multinomial logistic model is the probability of each outcome occurring. As our plot models have 3 distinct harvest removals, and each outcome is a probability of a specific event occurring while taking into account the likelihood of the other events occurring, the sum of the probability of the three events is the probability of a harvest occurring. This means that one minus the sum of all probable harvest types occurring equals the probability of no harvest. Equation 3 is the mathematical form of a statistical logistic model. The coefficient b_n represents the response of the odds of each type of harvest occurring corresponding to the the individual variables, which are represented by X_n. Specifically, b_0 represents the intercept.

$$Logistic\ Regression\ Probabilty = ln\left(\frac{p_i}{1-p_i}\right) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \cdots + b_nX_n \qquad \text{(Equation 3)}$$

where:

P is log of the odds of the event occurring.

b_n is the variable coefficient.

X_n is the slope of the coefficient.

Using the Models for Prediction

To determine which of the three categories of harvest is predicted, let P_i, be the probability of the i^{th} type of harvest. We draw a random number (x) uniformly distributed from [0,1]. If $x \leq P_1$, then harvest type 1 occurs. Otherwise, if $\sum_{i=1}^{j-1} P_i \leq x \leq \sum_{i=1}^{j} P_i$, then harvest type *j* occurs. Otherwise, if $x \geq \sum_{i=1}^{n} P_i$ (where *n* is the number of harvest types) then no harvest occurs. If a plot is selected for a harvest, the simulation will loop over each tree within the plot's tree list, and for each one the appropriate tree-level model will generate a probability that that tree will be harvested. Just as for the plot models, for each tree a random number between 0 and 1 will be drawn to determine whether the tree is harvested. In the tree models, however, there is only a binomial outcome of harvest or no-harvest. Therefore the random number uniformly distributed between zero and one is drawn, and if it less than the probability of a harvest occurring (from 0 to the probability) then a harvest occurs. If it is greater than that probability, a harvest does not occur.

This algorithm does not guarantee that when a plot is predicted to be in one of the three harvest categories, the corresponding percentage of the BA will actually end up being removed. For example, the plot could be selected for a low intensity thinning (≤20% of the BA removed), but the total BA of the trees actually selected for harvest could comprise more than 20% of the plot BA, or no trees could actually be selected for harvest. One could imagine several ways to revise the harvested tree list so that the result is always within the desired BA bound, or one could simply live with the tree selection that occurs in the first pass.

McFadden R^2

In order to assess the goodness of fit of all models, McFadden R^2 was used as a metric to determine the model fit. This metric is appropriate for logistic models since it uses the deviance of the model, versus a null model where the intercept is set to 1. By running a null model using 1 as the only variable, we create a deviance statistic for which there is no change in the predictor for the varying levels of response. Any reduction in variance due to good model fit then has a standard with which to compare. General interpretation of this metric for assessing absolute model fit is not recommended, however, as logistic models tend to have lower R^2 values than Gaussian regression models (Hosmer et al. 2013).

The McFadden R^2 is outlined in equation 4, below. The proportion of deviance between model and null model is calculated, and the value is then subtracted from 1. Better model fit occurs as McFadden R^2 approaches 1.

$$McFadden\ R^2 = 1 - \left(\frac{Deviance(Model)}{Deviance(Null\ Model)}\right) \qquad \text{(Equation 4)}$$

where:

McFadden R^2 is reported as proportion of variance explained by the model versus a null model.

Model is the model being evaluated.

Null Model is a model where a single model variable is set to 1.

Akaike Information Criterion

In the model selection process, the Akaike Information Criterion (AIC) was used to select final models based on the log-liklihood of that model versus similar models but reduced models. This metric, outlined in Equation 5, is not specifically interpretable beyond allowing for quantification of models for use in stepwise selection.

$$Akaike\ Information\ Criterion\ (AIC) = -2(log - likelihood) + 2K + \frac{2K\ (K+1)}{(n-K-1)} \qquad \text{(Equation 5)}$$

where:

AIC is the Akaike Information Criterion.

Log-Liklihood is the log-likelihood of the model

K is the # of model parameters.

And n is the number of observations.

Odds Ratio

The odds ratio in logistic modeling is how much more or less likely a predictive factor makes the outcome of occurring, per unit of that variable. It is created by exponentiating the variable coefficient. A value above one would be interpreted as the percentage more likely a harvest is to occur, for a change of one unit of the explanatory variable, and a number less than one would be what percentage less likely a harvest is to occur.

Public/Private Assessed Harvest Behavior

In addition to employing statistical models to research harvest behavior, valuable information could also be gained by looking at what is taken when a harvest occurs. The same datasets that informed statistical models also provided information on the impact of the harvest on stand characteristics, and specifically how tree composition and abundance changed with a harvest. Knowing the species, diameter and volume of trees that were harvested made it possible to assign value removed estimates.

The value of regeneration is not taken into account on these plots, as this is not the goal of the assessment, which is simply to track which trees were removed, and the underlying attributes associated with them compared with trees that were not removed. Using the actual plot values, rather than measuring value change between two cycles, we can more accurately determine how the change affects stand dynamics at a tree level.

Stand Value Change

The value of a tree can be assigned using the merchantable volume and tree market price. Any harvest that removes valuable trees reduces the total value from the stand. However, if lower-value species are harvested, in the long run this can increase the value of the stand as future growth is concentrated on trees with higher potential value. Some trees left behind in an improvement cut may be high-value species that currently have no value because they are too small to contain merchantable volume. Conversely, if higher-value species are removed, then the potential future value of the stand is reduced.

To get at whether a harvest resulted in a net improvement in the long-term value of a stand, we developed two indicators of stand value that may increase or decrease with a harvest: 1) plot value per square foot of basal area, and 2) plot value index per square foot of basal area. Value index is the species price times the basal area of a tree, rather than price times board feet, which would give plot value. This index reflects the value of trees that are valuable species but are too small to have merchantable volume, as board foot volume only occurs in hardwoods over 12 inches and softwoods over 9 inches, while basal area uses tree diameter. Both of these indexes are measures of a concept that could be described as "value density," or value per square foot of basal area. A harvest that improves the value density of a stand can be considered an "improvement" cut, while those that reduce value density can be considered a "diminishment" cut.

As covered in the literature review, the ownership of a timber stand affects the probability of harvesting activity. An interesting question is whether there is a difference between private and public ownerships with regard to whether harvests tend to improve or reduce the value of the stand. The FIA classifies ownership groups into two groups: *public and private*. The harvest behavior of both groups was examined using the natural hardwoods plots with 20% to 85% BA removed. This subset of the data was used because this harvest category represents thinnings that could have the greatest impact on future stand development and the natural hardwoods category was the most abundant forest type group. The analysis used two sample t-tests to assess whether there is a significant difference between public and private harvests, examining the characteristics of percent basal area removed, change in value per square foot of basal area removed, change in value index per square foot of basal area removed, and proportion of diameter removed to diameter remaining.

For testing the difference between means, an unequal variance was assumed with a two-tailed Welch t-test. The public/private, medium-heavily thinned, natural hardwood dataset consisted of 1,484 plots, with a 4:1 ratio of private to public. The mean of each population was also tested using a one-sample t-test, to determine if the percent change in value per square foot of basal area, and the proportion of the diameter of trees harvested to the overall plot average diameter (discussed in the next section) were significantly different from zero and one, respectively.

Diameter harvested versus overall average

Assuming a possible reduction in quality and value of a stand due to selective species harvesting, the average diameter of harvested trees may be higher or lower than the stand average diameter. Selecting larger-than-average diameter trees may be indicative of diameter-limit-cutting. The average diameter of trees removed from the plot is divided by the average diameter of all trees on the plot. This produced a proportion for harvested size versus stand size, where numbers above one indicated a harvest where trees larger than the average were taken, and trees under one indicated a harvest where trees smaller than the average were taken.

Chapter 4 - Results

Two types of information were gained from the analysis of data from our northeastern United States forests. The first is an examination of harvest behavior through the analysis of actual harvest activity observed from the cycle 1 dataset, and the second is a statistical examination of how environmental, economic, and social factors influence timber harvests.

Plot Model Analysis

Table 8 shows the McFadden R^2's for the five multinomial logistic regression models predicting the likelihood of harvesting a plot. Table 9 shows the coefficients of these models, the corresponding odds ratios, and the p-values for the test of whether the effect measured by the coefficient is statistically different from zero. McFadden R^2 was higher for softwood models, and are thus model fit was assumed to be low.

Table 8 - Plot level McFadden R^2, giving model goodness of fit for the five modeling categories.

PlotType	McFadden R^2
Artificial (Art)	0.108
Natural Aspen-Birch (NAB)	0.090
Natural Northern Hardwood (NNH)	0.061
Natural Oak-Hickory (NOH)	0.056
Natural Softwood (NatSf)	0.115

Results from the analysis of plot models (shown in table 9) reveals consistently strong significance across models for a variety of variables. Volume is a strongly correlated with harvest, most significantly cubic feet, compared to board foot volume. In general, though, the diameter and diameter^2 are more consistently significant overall. Site factors tend to be non-significant for high intensity harvests, likely due to the smaller number of plots receiving this type of harvest. Lower intensity harvests exhibit significance in access and operability factors that affect the difficulty in procuring or utilizing timber.

Many variable coefficients varied in sign and significance based on basal area removed. Latitude and longitude, was positive, but overwhelmingly significant only in the low to moderate intensity harvests. Population density was negatively correlated with harvests in all models, but only significant in moderate intensity harvests.

Table 9 - Coefficients, odds ratio and p values for the variables in the different developed models. Negative coefficients are highlighted in red, and significant p-values are highlighted in green.

Variable	Model	BA >85%			BA 85%>20%			BA <20%		
		Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*
Intercept	Art	-9.78		0.00	-6.31		0.00	-6.69		0.00
	NAB	-11.90		0.00	-6.87		0.00	-5.28		0.00
	NNH	-11.25		0.04	-8.36		0.00	-8.09		0.00
	NOH	-7.05		0.01	-8.06		0.00	-8.95		0.00
	NatSf	-18.76		0.00	-10.19		0.00	-10.70		0.00
Latitude (Decimal Degrees)	NNH	0.11	1.11	0.35	0.14	1.15	0.00	0.08	1.09	0.00
	NOH	-0.02	0.98	0.70	0.07	1.07	0.00	0.09	1.09	0.00
	NatSf	0.25	1.28	0.02	0.14	1.16	0.01	0.17	1.19	0.01
Longitude (Decimal Degrees)	NNH	0.02	1.02	0.55	0.02	1.02	0.00	0.00	1.00	0.49
	NatSf	-0.01	0.99	0.51	0.04	1.04	0.00	0.03	1.03	0.00
Slope (Percent)	Art	-0.05	0.95	0.09	-0.03	0.98	0.03	-0.01	0.99	0.36
	NAB	-0.05	0.96	0.02	-0.03	0.97	0.00	-0.01	0.99	0.55
	NNH	-0.03	0.97	0.12	-0.01	0.99	0.00	-0.01	0.99	0.00
	NOH	-0.04	0.96	0.01	-0.01	0.99	0.01	-0.01	0.99	0.00
	NatSf	-0.03	0.97	0.17	-0.01	0.99	0.41	0.00	1.00	0.57
Population Density ((Pop/Mile^2)/100)	Art	-0.75	0.47	0.08	-0.45	0.64	0.00	-0.02	0.98	0.78
	NAB	-0.02	0.98	0.91	-1.61	0.20	0.00	-0.16	0.85	0.45
	NNH	-0.01	0.99	0.90	-0.30	0.74	0.00	-0.02	0.98	0.48
	NOH	-0.04	0.96	0.48	-0.12	0.89	0.00	-0.01	0.99	0.65
	NatSf	-0.27	0.77	0.24	-0.24	0.79	0.01	-0.05	0.95	0.33
Distance to Mill (Miles)	Art	-0.10	0.90	0.03	-0.01	0.99	0.59	-0.01	0.99	0.55
	NAB	-0.01	0.99	0.67	-0.02	0.98	0.05	-0.02	0.98	0.18
	NNH	0.02	1.02	0.55	0.02	1.02	0.00	-0.03	0.97	0.01
	NOH	-0.06	0.94	0.08	-0.04	0.96	0.00	-0.02	0.98	0.00
	NatSf	-0.02	0.98	0.32	0.00	1.00	0.73	-0.04	0.96	0.02
Distance to Road (Miles)	Art	-0.09	0.92	0.86	-0.17	0.85	0.51	-0.76	0.47	0.18
	NAB	-0.25	0.78	0.20	-0.23	0.80	0.04	-0.14	0.87	0.34
	NNH	-0.13	0.88	0.69	-0.18	0.84	0.02	-0.56	0.57	0.00
	NOH	-0.09	0.91	0.81	-0.07	0.93	0.49	-0.36	0.70	0.01
	NatSf	-0.16	0.85	0.39	-0.29	0.75	0.01	-0.58	0.56	0.00

Variable	Model	BA >85%			BA 85%>20%			BA <20%		
		Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*
Value per Ft^2 (($BFAcre/1000)/(BA/100))	NAB	-2.45	0.09	0.01	0.08	1.08	0.84	0.61	1.84	0.14
	NNH	0.14	1.15	0.33	0.09	1.10	0.05	0.01	1.01	0.90
	NOH	0.04	1.04	0.89	0.35	1.42	0.00	0.22	1.25	0.00
	NatSf	1.57	4.81	0.00	0.99	2.70	0.00	-0.18	0.84	0.64
Owner(Public)	Art	-0.88	0.41	0.05	-0.55	0.58	0.01	-0.59	0.55	0.03
	NAB	-0.16	0.85	0.56	-0.34	0.71	0.03	-0.88	0.41	0.00
	NNH	-0.51	0.60	0.32	-1.32	0.27	0.00	-1.17	0.31	0.00
	NOH	0.69	1.99	0.20	-0.23	0.80	0.21	-1.46	0.23	0.00
	NatSf	-0.35	0.70	0.32	-0.80	0.45	0.00	-0.65	0.52	0.00
Owner(Public)*Value	NOH	-0.84	0.43	0.15	-0.46	0.63	0.00	0.14	1.16	0.23
Basal Area per Acre (Feet^2/100)	Art	-0.12	0.89	0.90	1.10	3.01	0.01	1.81	6.13	0.00
	NOH	-0.44	0.65	0.43	0.08	1.09	0.59	0.89	2.43	0.00
	NatSf	-2.21	0.11	0.01	-0.59	0.55	0.05	0.52	1.68	0.12
Board Feet per Acre (Feet/1000)	NOH	-0.01	0.99	0.82	0.02	1.02	0.23	-0.05	0.95	0.00
	NatSf	-0.36	0.69	0.00	-0.09	0.91	0.03	0.01	1.01	0.80
Cubic Feet per Acre (Feet^3/1000)	Art	0.13	1.14	0.74	-0.17	0.84	0.35	-0.57	0.56	0.05
	NAB	0.25	1.29	0.12	0.33	1.40	0.00	0.46	1.58	0.00
	NNH	-0.14	0.87	0.57	0.21	1.24	0.00	0.28	1.32	0.00
	NatSf	1.98	7.24	0.00	0.67	1.95	0.01	-0.04	0.96	0.90
Average Diameter (DBH Inches)	Art	1.80	6.05	0.02	1.01	2.75	0.00	0.77	2.16	0.02
	NAB	1.70	5.48	0.00	1.17	3.23	0.00	0.70	2.01	0.01
	NNH	0.44	1.56	0.27	0.31	1.36	0.01	0.40	1.49	0.01
	NOH	0.55	1.74	0.05	0.46	1.58	0.00	0.46	1.58	0.00
	NatSf	0.50	1.66	0.20	1.25	3.50	0.00	0.48	1.61	0.02
Average Diameter^2 (DBH Inches)	Art	-0.10	0.91	0.03	-0.06	0.94	0.00	-0.03	0.97	0.08
	NAB	-0.07	0.93	0.03	-0.07	0.93	0.00	-0.06	0.94	0.00
	NNH	-0.01	0.99	0.52	-0.01	0.99	0.03	-0.02	0.98	0.01
	NOH	-0.02	0.98	0.15	-0.02	0.98	0.00	-0.02	0.98	0.00
	NatSf	-0.03	0.97	0.23	-0.09	0.91	0.00	-0.03	0.97	0.04
Hardwoods	Art	-0.92	0.40	0.17	-0.60	0.55	0.04	-0.42	0.66	0.19
Southern Pines	Art	0.44	1.56	0.30	0.33	1.39	0.12	-1.31	0.27	0.00
Oak - Pine	NOH	1.18	3.26	0.00	0.43	1.54	0.00	-0.03	0.97	0.84
Other HdWd/Swamp Forest	NOH	-0.53	0.59	0.27	-0.67	0.51	0.00	-0.70	0.50	0.00
Northern Pines - Hemlock	NatSf	1.23	3.42	0.00	0.61	1.85	0.00	1.00	2.72	0.00
Southern Pines - Other Conifers	NatSf	2.09	8.07	0.02	0.83	2.28	0.05	0.67	1.95	0.23

Location

Latitude and longitude tend to be significant and positive in natural hardwood models for less than 20% BA removed and between 20% to 85% BA removed. This suggests the further east and north a plot is the more likely that plot is to undergo a harvest. For example, for moderate intensity northern hardwood harvests, the probability of a harvest increases by 15% for each degree of latitude increased and 3% for each degree of longitude.

Distance to a mill and distance to an improved road are also important factors, given their significance and consistency. Distance to mill tends to be significantly negative for low and moderate intensity harvests, which may be due to an overall trend of access and operability factors being significant when few trees were removed from a plot. This equates to a reduced probability of harvest the further from a lumber mill the plot is. Distance to road is also significantly negative for low and medium intensity harvests, suggesting that more remote stands are significantly less likely to be harvested. Population density is negatively related with harvest probability in nearly all harvesting models, but it is only statistically significant in moderate harvest intensity models.

Plot slope is also consistently negatively related to harvesting overall. Plots with steeper slopes are less likely to be harvested in all models where it is significant. On average, a one degree increase in slope causes a 3% reduction in harvest probability. This negative harvest probability effect is strongest as the basal area removed increases.

Ownership

The category of ownership is influential in determining harvest frequency according to previous literature (Butler and Leatherberry 2004). The analysis here suggests a similar result, with public ownership correlating to a decreased probability of a harvest, specifically reducing the odds of being harvested by 50% to 75% in significant cases. This effect is more statistically significant for plots where a lower volume of timber was harvested. Interacting public ownership with value gave significant results only in the moderate intensity harvests of Natural Oak-Hickory stands, suggesting that public owners are less influenced by value for those stands.

Value Per Square Foot of Basal Area

Value per square foot of basal area tends to be positively related to harvesting likelihood when statistically significant. The one exception is overstory removal harvests on natural aspen-birch plots. The significance of plot value in some of the models suggests that harvesting occurs with monetary goals in mind. Value per square foot of basal area was not significant on artificially-regenerated plots. The variable was generally significant and positively related to the probability of harvest for natural stands – except aspen-birch. This effect was strongest in natural softwood stands.

Diameter/Volume

Diameter and diameter^2 are both strongly significant across almost all models, making them valuable in predicting whether a stand is likely to undergo a harvest. The strong non-linear response in harvest likelihood to the average diameter suggests that stands with very large trees are less likely to be harvested. A possible explanation for this is that the presence of very large trees indicates that timber management is not a high priority for the owners of those stands. Consequently, the likelihood that a stand will be harvested tends to increase with diameter up to a point of maximum likelihood and then it declines. Diameter tended to be most strongly significant in moderate intensity harvests, and the squared effect of diameter is strongest in artificial and natural aspen-birch stands.

Plot volume in feet^3/acre tends to be significantly positively related to the probability of medium intensity thinnings on natural-origin stands, but negatively related to the probability of thinnings on artificial stands. In moderate intensity harvests, the odds ratio indicates that each thousand cubic feet increase in volume improves the probability of a harvest by between 25%-95%. Somewhat unexpectedly, board foot volume, which is only greater than zero on trees 9 inches or larger for softwoods and 12 inches or larger for hardwoods, was negatively related to harvesting when it was significant. This is likely reinforced by cubic foot, board foot, basal area, and diameter are all being highly correlated. Higher basal area, which is a measure of the density of a stand, tended to be significantly positive for thinnings, increasing the odds of harvest on artificial stands, and significantly negative for overstory removal harvests. Higher basal area makes a low intensity harvest more likely, and a high intensity harvest less likely.

Forest Type

The effect of forest type varied across models due to different forest type groupings being used within those models. In artificial plots, southern pine plots were less likely to be harvested than northern pines in low intensity harvests, while hardwoods were less likely to be harvested in moderate intensity harvests. In the broad oak-hickory modeling category, oak-hickory stands were less likely to be harvested in moderate-to-high intensity harvests than oak-pine stands, but more likely to be harvested than swamp-forest stands in moderate-to-low intensity harvests. In the natural softwoods model, spruce-fir was significantly less likely than northern pines-hemlock to be harvested at all intensities, and significantly less likely than southern pines-other conifers in moderate-to-high intensity harvests.

Tree Model Analysis

Table 10 shows the McFadden R^2's for the 30 logistic regression models of the likelihood of a tree being harvested. Table 11 shows the coefficients of these models, the corresponding odds ratios, and the p-values for the test of whether the effect measured by the coefficient is statistically different from 0. Tree-level models utilized a smaller variable list than plot-level models. The overall result was consistent effects and significance within volume variables, with varied effects and significance among species.

McFadden R^2 was higher overall in individual tree models than plot models, suggesting that model fit for tree harvests is less difficult than plot-level harvests, using model fit as a reference. Best model fit was in the high harvest intensity categories of natural aspen-birch and natural softwoods, and artificial plots on publically held land. Model fit was generally higher the higher the harvest intensity, suggesting that more likely events – such as a tree being harvested in a plot where more than 85% of the basal area is being removed – are easier to predict than less likely events – such as a tree being harvested in a plot where less than 20% of the basal area is being removed.

Table 10 - McFadden R^2s for 30 tree-level models, showing goodness of fit of each model.

Ownership	PlotType	BA>85%	85%>BA>20%	BA<20%
Private	Artificial	0.277	0.074	0.113
Private	NaturalAB	0.423	0.219	0.056
Private	NaturalNH	0.232	0.124	0.052
Private	NaturalOH	0.275	0.118	0.031
Private	NaturalSoftwood	0.321	0.168	0.074
Public	Artificial	0.641	0.071	0.112
Public	NaturalAB	0.527	0.198	0.049
Public	NaturalNH	0.235	0.064	0.019
Public	NaturalOH	0.314	0.127	0.057
Public	NaturalSoftwood	0.415	0.159	0.080

Diameter/Volume

Diameter and diameter^2 were the strongest predictors in the tree models (Table 11). They were significant in all but one of the models, and in that model, public natural oak-hickory, the p-value for diameter^2 was 0.061. The parameter values also showed a consistent nonlinear pattern as in the plot level models.

Cubic feet was also consistently significant and positive. The odds ratios for this variable suggested the largest increase in harvest odds due to this variable occurs in high-intensity harvests in natural aspen-birch stands.

Cull

Cull was negatively related to harvest probability in all of the private tree harvest models and in most public tree harvest models. In most cases it is significantly different from zero, and when the coefficient is negative, it is generally significantly different from zero, with the one exception of overstory removal harvests on publicly-owned natural aspen-birch stands. Thus, in most models trees with a higher percentage of dead wood are less likely to be harvested, with the overall average of each percentage increase in cull reducing the probability of harvest by roughly 3% on average. By contrast, while not significant, the estimated cull coefficients for overstory removal harvests on public land are positive and large, suggesting that trees with a large proportion of cull are almost certain to be harvested in those instances.

Species

Timber species significance varied considerably among different tree models. The goal in modeling species was to examine harvest trends for individual species depending on which forest type they occurred. This can work to explain which species are targeted depending on forest type. White oak, for example, is consistently less likely to be harvested in moderate to heavy thinnings, regardless of forest type. Spruce-fir has roughly a 50% less chance to be harvested than aspen in a natural aspen-birch stand, regardless of harvest type. Aspen trees are 2-3 times more likely to be harvested than sugar maple on natural northern hardwood plots. Red maple on natural oak-hickory stands in low to moderate intensity harvests is also 2-3 times more likely to be harvested than sugar maple. Elm is almost 75% less likely to be harvested in the majority of moderate intensity harvests. Other softwoods are half as likely to be harvested in natural stands overall.

Table 11 - Statistical output, including coefficients, odds ratios and p-values for 30 tree-level models. Negative coefficients are shown in red, and significant p-values are shown in green.

		Private									Public								
		BA>85%			85%>BA>20%			BA<20%			BA>85%			85%>BA>20%			BA<20%		
Variable	PlotType	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*
Intercept	Art	-1.24		0.03	-2.59		0.00	-2.64		0.00	-9.83		0.00	-3.4		0.00	-2.69		0.00
	NatAB	-1.09		0.00	-3.71		0.00	-3.01		0.00	-2.67		0.00	-3.14		0.00	-5.19		0.00
	NatNH	-0.51		0.13	-3.41		0.00	-4.59		0.00	-1.57		0.01	-2.46		0.00	-3.74		0.00
	NatOH	-0.25		0.56	-2.72		0.00	-4.14		0.00	-2.45		0.00	-2.24		0.00	-3.02		0.00
	NatSoft	-0.95		0.05	-3.15		0.00	-4.29		0.00	-4.94		0.00	-3.73		0.00	-4.27		0.00
Cubic Feet (Ft^3 Volume)	Art	0.06	1.06	0.00	0.02	1.02	0.00				0.64	1.9	0.00	0.03	1.03	0.00	0.04	1.04	0.01
	NatAB	0.21	1.24	0.00	0.05	1.05	0.00	0.03	1.03	0.00	0.25	1.29	0.00	0.05	1.05	0.00	0.04	1.04	0.01
	NatNH	0.01	1.01	0.10	0.01	1.01	0.00	0.00	1	0.22	0.08	1.08	0.00	0.01	1.01	0.00	0.01	1.01	0.02
	NatOH	0.05	1.05	0.00	0.01	1.01	0.00				0.19	1.21	0.00	0.03	1.03	0.00			
	NatSoft	0.09	1.1	0.00	0.01	1.01	0.00	0.00	1	0.35	0.20	1.23	0.00	0.04	1.05	0.00	0.01	1.01	0.20
Diameter (DBH Inches)	Art	0.95	2.59	0.00	0.62	1.86	0.00	0.17	1.18	0.04	4.62	101.9	0.00	0.73	2.07	0.00	0.62	1.86	0.00
	NatAB	1.27	3.56	0.00	0.98	2.67	0.00	0.27	1.31	0.00	1.53	4.6	0.00	0.86	2.35	0.00	0.72	2.06	0.00
	NatNH	0.47	1.61	0.00	0.44	1.55	0.00	0.32	1.38	0.00	0.85	2.33	0.00	0.37	1.44	0.00	0.40	1.49	0.00
	NatOH	0.48	1.62	0.00	0.29	1.33	0.00	0.17	1.19	0.00	1.29	3.63	0.00	0.53	1.69	0.00	0.15	1.16	0.03
	NatSoft	0.72	2.06	0.00	0.66	1.94	0.00	0.5	1.65	0.00	2.11	8.27	0.00	1.1	2.99	0.00	0.55	1.74	0.00
$Diameter^2$ (DBH Inches)	Art	-0.08	0.92	0.00	-0.05	0.95	0.00	-0.01	0.99	0.05	-0.71	0.49	0.00	-0.06	0.94	0.00	-0.07	0.93	0.00
	NatAB	-0.21	0.81	0.00	-0.08	0.92	0.00	-0.03	0.97	0.00	-0.25	0.78	0.00	-0.07	0.93	0.00	-0.07	0.94	0.00
	NatNH	-0.02	0.98	0.00	-0.02	0.98	0.00	-0.01	0.99	0.00	-0.08	0.92	0.00	-0.02	0.98	0.00	-0.03	0.97	0.00
	NatOH	-0.05	0.96	0.00	-0.01	0.99	0.00	0.00	1	0.00	-0.18	0.83	0.00	-0.04	0.96	0.00	-0.01	0.99	0.06
	NatSoft	-0.09	0.91	0.00	-0.04	0.96	0.00	-0.02	0.98	0.00	-0.25	0.78	0.00	-0.09	0.91	0.00	-0.04	0.96	0.00
Cull (% dead wood)	Art	-0.07	0.93	0.00	-0.02	0.98	0.00	-0.09	0.91	0.13	11.78	1E+05	0.99	-0.03	0.97	0.09	-1.17	0.31	0.16
	NatAB	-0.02	0.98	0.14	-0.01	0.99	0.01	-0.01	0.99	0.33	0.13	1.14	0.05	0.01	1.01	0.23	0.00	1	0.94
	NatNH	-0.05	0.95	0.00	-0.03	0.97	0.00	-0.02	0.98	0.00	-0.06	0.95	0.04	-0.03	0.98	0.00	0.00	1	0.73
	NatOH	-0.01	0.99	0.03	-0.02	0.98	0.00	-0.01	0.99	0.06	15.02	3E+06	0.99	-0.01	0.99	0.09	-0.01	0.99	0.50
	NatSoft	-0.02	0.98	0.00	-0.04	0.96	0.00	-0.03	0.97	0.00	12.43	3E+05	0.98	-0.03	0.97	0.04	-0.05	0.95	0.17

Variable	PlotType	Private									Public								
		BA>85%			85%>BA>20%			BA<20%			BA>85%			85%>BA>20%			BA<20%		
		Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*
Species American Beech	Art				0.40	1.49	0.34				-5.24	0.01	0.01						
	NatAB	-1.66	0.19	0.31	-1.12	0.33	0.15	1.38	3.96	0.00				0.87	2.39	0.6			
	NatNH				0.82	2.27	0.00	0.52	1.69	0.00				0.07	1.07	0.66			
	NatOH	-0.25	0.78	0.72	-0.13	0.88	0.33	0.21	1.23	0.47				-0.42	0.66	0.23	-15	0.00	0.99
	NatSoft				-2.30	0.10	0.00	-0.32	0.72	0.54				-15.8	0.00	0.99	-13.9	0.00	0.99
Species Ash	Art	12.16		1	0.12	1.12	0.65				26.58	3E+11	1	-14.1	0.00	0.98	-16.8	0.00	0.99
	NatAB	-1.04	0.35	0.03	-1.32	0.27	0.00	-0.67	0.51	0.16	-1.25	0.29	0.02	-2.66	0.07	0.00			
	NatNH				0.11	1.11	0.23	0.4	1.49	0.00				0.17	1.18	0.49			
	NatOH	1.44	4.24	0.07	0.02	1.02	0.83	0.51	1.67	0.00				-0.59	0.56	0.01	-0.88	0.42	0.11
	NatSoft	-17.8	0.00	0.99	-1.43	0.24	0.00	-0.95	0.39	0.04				0.78	2.17	0.37	-13.5	0.00	0.98
Species Aspen	Art	-0.44	0.64	0.47	0.29	1.34	0.26				-1.76	0.17	0.37	0.73	2.07	0.00	-0.49	0.61	0.25
	NatNH				1.22	3.40	0.00	0.96	2.60	0.00				0.70	2.01	0.00			
	NatOH	-1.16	0.31	0.07	0.80	2.22	0.00	0.68	1.98	0.00				0.44	1.55	0.01	1.11	3.04	0.00
	NatSoft	0.60	1.81	0.44	-0.23	0.80	0.15	0.25	1.28	0.32				-0.19	0.83	0.35	-0.27	0.76	0.56
Species Birch	Art	0.01	1.01	0.99	-0.69	0.50	0.25				1.32	3.75	0.73	-1.28	0.28	0.09	-1.33	0.27	0.22
	NatAB	-0.48	0.62	0.22	-0.16	0.85	0.13	-0.14	0.87	0.46	-0.54	0.58	0.14	-0.21	0.81	0.09			
	NatNH				0.66	1.94	0.00	0.61	1.84	0.00				0.16	1.18	0.52			
	NatOH	-0.29	0.75	0.84	0.55	1.74	0.00	0.22	1.24	0.27				-0.20	0.82	0.37	0.23	1.26	0.72
	NatSoft	-0.72	0.49	0.17	-0.61	0.54	0.00	0.12	1.12	0.60				0.09	1.10	0.73	1.26	3.52	0.00
Species Elm	Art	-17.7	0.00	0.99	-0.43	0.65	0.26				26.05	2E+11	1	-0.54	0.58	0.50	1.91	6.74	0.2
	NatAB	-0.38	0.68	0.75	-2.53	0.08	0.00	0.75	2.12	0.18	15.51	5E+06	0.99	-1.70	0.18	0.00			
	NatNH				-0.18	0.84	0.36	0.8	2.23	0.00				0.89	2.44	0.29			
	NatOH	0.14	1.15	0.81	-0.75	0.47	0.00	0.45	1.57	0.00				-2.62	0.07	0.01	-0.50	0.6	0.63
	NatSoft	-0.90	0.41	0.36	-3.00	0.05	0.00	0.52	1.69	0.35				-15.7	0.00	0.99			
Species Hickories	Art	16.5		0.99	0.44	1.55	0.21							-14.7	0.00	0.98			
	NatAB				-0.55	0.58	0.47	-15.3	0.00	1									
	NatNH				-0.06	0.95	0.80	-0.5	0.61	0.24				-14.3	0.00	0.98			
	NatOH	-0.79	0.45	0.15	-0.63	0.53	0.00	-0.17	0.84	0.31				-2.01	0.13	0.00	-1.68	0.19	0.10
	NatSoft	-0.11	0.89	0.93	0.08	1.08	0.88	-14.7	0.00	0.99				-17.1	0.00	0.98			

		Private									Public								
		BA>85%			85%>BA>20%			BA<20%			BA>85%			85%>BA>20%			BA<20%		
Variable	PlotType	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*
Species Miscellaneous Hardwoods	Art	0.90	2.46	0.11	0.1	1.11	0.56							-0.54	0.58	0.62	-17.4	0.00	0.99
	NatAB	11.93		0.99	-0.87	0.42	0.06	-0.09	0.91	0.88	13.22	6E+05	0.99	-1.82	0.16	0			
	NatNH				-0.15	0.86	0.13	-0.01	0.99	0.94				0.14	1.15	0.43			
	NatOH	0.44	1.55	0.30	-0.30	0.74	0.00	0.15	1.16	0.26				-1.18	0.31	0	-0.15	0.86	0.71
	NatSoft	2.59	13.29	0.00	-0.52	0.59	0.04	-0.50	0.60	0.35				-1.99	0.14	0.07	-13.9	0.00	0.99
Species Non-Canopy/ Non-Commerical	Art	-1.08	0.34	0.10	0.06	1.06	0.82							-1.2	0.3	0.25	-16.6	0.00	0.99
	NatAB	-1.37	0.25	0.02	-1.18	0.31	0.00	-0.32	0.72	0.5	-1.98	0.14	0.08	-2.59	0.07	0.01			
	NatNH				0.10	1.11	0.39	0.48	1.62	0.01				0.03	1.03	0.92			
	NatOH	1.46	4.29	0.01	-0.16	0.85	0.09	0.55	1.73	0				-1.29	0.28	0.00	-0.30	0.74	0.59
	NatSoft	0.26	1.30	0.73	-0.24	0.78	0.11	0.05	1.05	0.87				-14.2	0	0.96	-13.1	0.00	0.99
Species Other Red Oak	Art	-0.35	0.7	0.69	-0.45	0.64	0.16				29.39	6E+12	1	0.83	2.3	0.08	0.51	1.66	0.39
	NatAB				-13.5	0.00	0.97												
	NatNH				-11.7	0.00	0.93	-11.1	0.00	0.94									
	NatOH	-0.29	0.75	0.58	0.12	1.13	0.14	0.54	1.72	0				0.42	1.52	0.02	-0.04	0.96	0.92
	NatSoft	-1.67	0.19	0.00	-0.25	0.78	0.52	-14.7	0.00	0.98				0.54	1.71	0.62	0.12	1.13	0.91
Species Other Softwoods	Art	0.12	1.13	0.88	1.98	7.21	0.01				16.26	1E+07	1	-6.2	0	1	-17.2	0.00	1
	NatAB	-2.17	0.11	0.02	-0.60	0.55	0.00	0.76	2.14	0	14.6	2E+06	0.99	-1.41	0.24	0.00			
	NatNH				-0.14	0.87	0.09	-0.62	0.54	0				-1.14	0.32	0.00			
	NatOH	1.25	3.47	0.26	-0.79	0.45	0.00	-0.04	0.96	0.83				-0.36	0.7	0.52	-15.3	0.00	0.98
	NatSoft	3.51	33.58	0.00	-0.39	0.68	0.00	-1.15	0.32	0				-0.99	0.37	0.00	-0.25	0.78	0.35
Species Other Valuable Hardwood	Art	0.61	1.85	0.67	-0.14	0.87	0.61				-1.13	0.32	0.84	-0.76	0.47	0.26	-17	0.00	0.99
	NatAB	-2.20	0.11	0.04	-1.21	0.3	0.00	-0.01	0.99	0.99	-4.59	0.01	0.58	-1.76	0.17	0.01			
	NatNH				0.13	1.14	0.04	0.26	1.29	0.04				-0.55	0.58	0.00			
	NatOH	-0.28	0.75	0.62	-0.17	0.84	0.11	0.46	1.58	0				-1.58	0.21	0.00	-0.92	0.40	0.22
	NatSoft	-0.83	0.44	0.45	-0.51	0.6	0.00	-0.37	0.69	0.27				-1.9	0.15	0.00	0.04	1.04	0.95
Species White Oak	Art				-1.36	0.26	0.03							-0.98	0.38	0.20	-16.8	0.00	1
	NatAB	-17.2	0.00	0.97	-1.86	0.16	0.00	-15.1	0	0.98	13.94	1E+06	1	-2.14	0.12	0.01			
	NatNH				-1.67	0.19	0.03	1.22	3.39	0.03									
	NatOH	0.52	1.69	0.47	-0.18	0.83	0.05	0.10	1.11	0.48				-0.49	0.61	0.02	-0.6	0.55	0.21
	NatSoft	-16.2	0.00	0.99	-2	0.14	0.00	1.31	3.69	0.14				15.66		0.99	-14.4	0.00	0.99

Variable	PlotType	Private									Public								
		BA>85%			85%>BA>20%			BA<20%			BA>85%			85%>BA>20%			BA<20%		
		Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*	Coef	Odds	P*
Species Red & White Pine	NatAB	-1.41	0.24	0.28	-2.11	0.12	0.00	-16.4	0.00	0.97	-16.7	0.00	0.99	-2.55	0.08	0.00			
	NatNH				0.24	1.27	0.19	0.33	1.40	0.13				0.29	1.34	0.37			
	NatOH	-0.93	0.39	0.12	-0.07	0.93	0.49	0.58	1.79	0.00				-0.67	0.51	0.00	0.04	1.04	0.92
	NatSoft	2.88	17.77	0.00	-0.52	0.6	0.00	-0.77	0.46	0.00				-1.32	0.27	0.00	-0.80	0.45	0.01
Species Red Maple	Art	1.17	3.24	0.07	-0.16	0.85	0.46				3.61	36.81	0.06	-0.44	0.65	0.30	-0.60	0.55	0.38
	NatAB	0.82	2.26	0.08	-0.83	0.43	0.00	-0.28	0.76	0.27	1.68	5.39	0.00	-0.56	0.57	0.00			
	NatNH				0.37	1.45	0.00	0.30	1.35	0.00				0.33	1.39	0.00			
	NatSoft	-0.04	0.96	0.92	-0.74	0.48	0.00	-0.36	0.7	0.07				-0.35	0.70	0.12	0.24	1.27	0.61
Species Southern-Jack Pine	Art	-0.97	0.38	0.00	0.51	1.67	0.00				-0.15	0.86	0.90	1.27	3.56	0.00	0.81	2.24	0.07
	NatAB				0.96	2.61	0.01	0.09	1.10	0.90				-0.55	0.57	0.29			
	NatNH				-11.8	0	0.97	-10.9	0.00	0.98									
	NatOH	-0.50	0.60	0.30	0.82	2.28	0.00	1.12	3.06	0.00				1.20	3.33	0.01	-15.5	0.00	0.99
	NatSoft	0.44	1.56	0.08	-0.03	0.97	0.7	-0.61	0.54	0.01				0.22	1.24	0.11	-1.19	0.30	0.01
Species Spruce-Fir	Art	-0.29	0.75	0.65	-0.66	0.52	0.01				1.41	4.10	0.42	0.75	2.12	0.00	-0.81	0.44	0.01
	NatAB	-0.68	0.51	0.01	-0.37	0.69	0.00	-1	0.37	0.00	-0.42	0.66	0.13	-0.39	0.67	0.00			
	NatNH				1	2.72	0.00	0.58	1.79	0.00				0.11	1.12	0.54			
	NatOH	-2.17	0.11	0.00	0.64	1.89	0.00	0.59	1.81	0.02				-0.73	0.48	0.10	-0.95	0.39	0.21
Species Sugar Maple	Art	15.36		0.99	1.02	2.77	0.09				-23.4	0.00	1	-13.6	0.00	0.98	-16.7	0.00	0.99
	NatAB	-1.16	0.31	0.08	-0.37	0.69	0.13	0.06	1.06	0.90	3.69	39.92	0.00	-1.52	0.22	0.00			
	NatOH	0.38	1.46	0.61	-1.06	0.35	0.00	-0.11	0.89	0.59				0.13	1.14	0.64	0.05	1.05	0.91
	NatSoft				-1.09	0.34	0.01	-14.4	0.00	0.96				-1.18	0.31	0.11	0.83	2.30	0.16
Species Valuable Red Oak	Art	15.34		0.98	0.08	1.08	0.79				-17.3	0.00	1	1.34	3.83	0.01	-17.1	0.00	0.99
	NatAB	-0.65	0.52	0.44	-2.98	0.05	0.00	1.14	3.11	0.00	-0.07	0.94	0.95	-0.97	0.38	0.00			
	NatNH				0.29	1.33	0.02	0.44	1.55	0.01				-0.56	0.57	0.07			
	NatOH	-1.42	0.24	0.02	-0.03	0.97	0.67	0.26	1.30	0.06				-0.21	0.81	0.13	0.11	1.11	0.73
	NatSoft	1.01	2.74	0.38	-1.14	0.32	0.00	-0.29	0.75	0.42				-0.51	0.60	0.13	-0.37	0.69	0.63

		Private									Public								
		BA>85%			85%>BA>20%			BA<20%			BA>85%			85%>BA>20%			BA<20%		
Variable	**PlotType**	**Coef**	**Odds**	**P***	**Coef**	**Odds**	**P***	**Coef**	**Odds**	**P***	**Coef**	**Odds**	**P***	**Coef**	**Odds**	**P***	**Coef**	**Odds**	**P***
Species White Oak	Art	1.43	4.18	0.23	0.17	1.19	0.49							-12.4	0.00	0.99	-16.8	0.00	0.99
	NatAB				-13.6	0.00	0.95	-15.3	0.00	0.99				-0.46	0.63	0.55			
	NatNH				-0.29	0.75	0.39	-0.22	0.80	0.83				-14.1	0.00	0.98			
	NatOH	0.30	1.36	0.54	-0.10	0.90	0.20	0.14	1.15	0.33				-1.23	0.29	0.00	0.05	1.05	0.88
	NatSoft	12.78		0.99	-0.56	0.57	0.23	-1.11	0.33	0.28				-0.79	0.45	0.39			
Species Yellow-Poplar	Art	0.91	2.49	0.12	0.00	1	0.99							-1.14	0.32	0.33			
	NatNH				0.13	1.13	0.66	-0.68	0.51	0.36				-14.6	0.00	0.97			
	NatOH	2.30	9.97	0.03	0.17	1.18	0.10	0.31	1.36	0.09				-0.84	0.43	0.08	0.44	1.56	0.37
	NatSoft	13.49		0.98	-0.57	0.56	0.07	-14.8	0.00	0.98				-18.2	0.00	0.99			

Public/Private Harvest Index

Assessment of percent change in value per square foot basal area on harvested plots showed that the pattern of value removed from private plots differed significantly from public plots. Figure 6 shows a scatterplot of natural hardwood plots with between 20 and 85% of the basal area removed. The vertical axis of the graph shows the percent change in value per square foot of basal area. Positive values indicate that the harvest increased the value per square foot of basal area, while negative values indicate that the harvest decreased the value per square foot of basal area. Reductions of up to 100% are possible if the remaining trees have no value. This could happen if the remaining trees are too small to have merchantable board foot volume. Increases in value per square foot are possible if small or lower-value trees are removed. Possible increases in value per square foot are limited if only a small percent of the basal area is removed. This is why there are no points in the upper right corner of the graph.

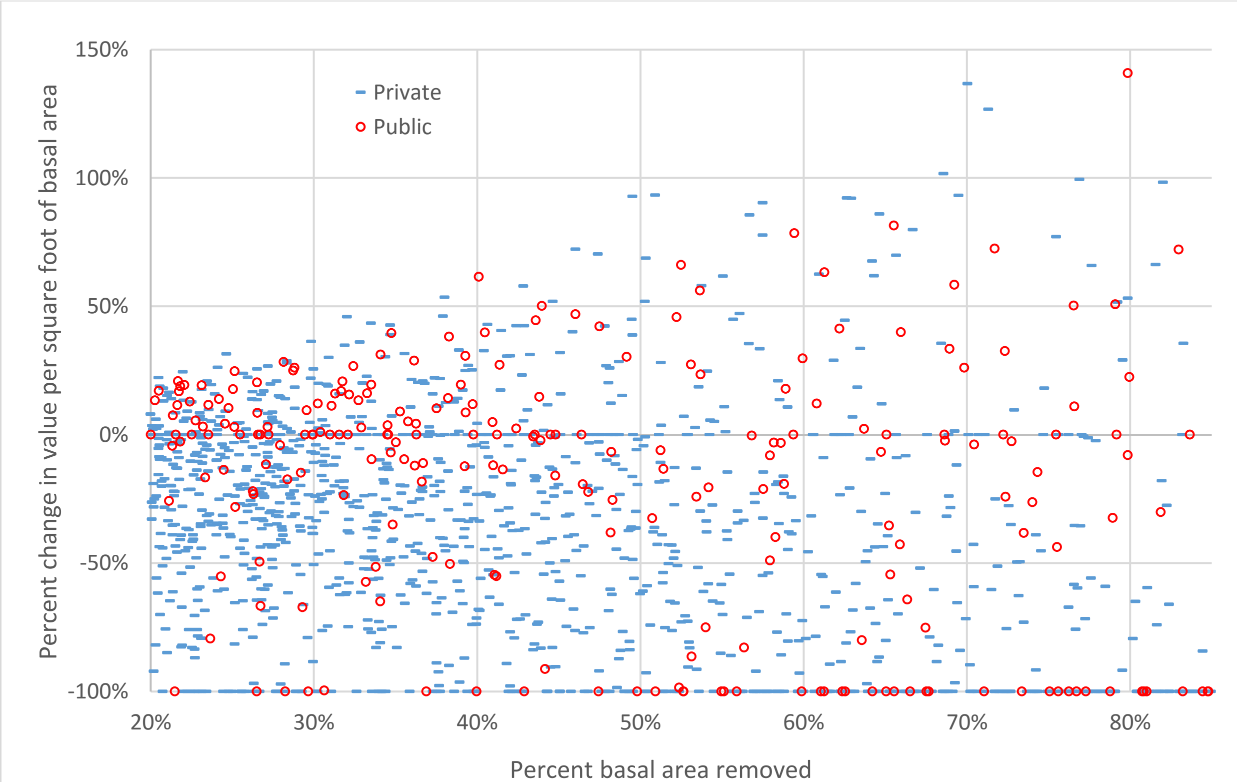

Figure 6 - Percent change in value per ft^2 versus percent of basal area removed on natural hardwood FIA plots where more than 20% and less than 85% of the basal area was removed. by public and private ownership.

While both ownership categories have plots above and below the 0% change line, private plots are much more likely to be below the line than above it while public plots are only slightly more likely to be below the line. This result was confirmed statistically by calculating the average percent change in value per ft^2 of basal area for both ownerships. As shown in Table 12, the average percent change in value per ft^2 of basal area for private plots was -33.1%, while the average percent change in value per ft^2 of basal area for public plots was only -11.8%. These values are both significantly different from zero and from each other.

Unless the trees removed have no value, harvests will always decrease the total value of a stand. Harvests also always decrease the basal area of a stand. This is why the value per square foot of basal area can go up or down after a harvest. Each tree has a value and represents a certain amount of the square foot basal area of the stand. If a tree that has a value per square foot of basal area that is lower than the stand average is harvested, this will increase the value per square foot of the residual stand. If a tree that has a value per square foot that is higher than the stand average is harvested, then the value per square foot of the residual stand is decreased. The value per square foot of a tree tends to be higher if the tree is a high value species. It also tends to be higher for larger trees. For trees that are too small to have any board foot volume, the value per square foot of basal area is zero. As a tree grows past the minimum diameter for sawtimber, its value becomes positive. After that, it will tend to put on board foot volume at a faster rate than it increases in basal area. Thus, trees vary in terms of their value per ft^2 of basal area for two reasons: 1) because different species have different values, and 2) because larger trees have more value per ft^2 of basal area than small trees. Thus a harvest may decrease the average value per ft^2 of basal area for two reasons: 1) because higher-value species are more likely to be removed, or 2) because larger trees are more likely to be removed.

The first reason is more of a concern than the second. If larger trees are being removed, but the species composition of the stand is not being changed, then once the smaller trees grow larger, the stand likely will recover in value. On the other hand, if the higher-value species are being removed from the stand, then it is unlikely that the stand will recover its value. The purpose of the "value index" measure used in this thesis is to eliminate the size effect to allow us to focus on the species effect. Thus the value index is based on the price per board foot of a given species, but rather than multiplying this price times board foot volume, it is multiplied by the basal area of the tree. This index values a board foot of basal area the same whether it is from a small tree or a large tree and therefore removes the size effect from the value measure.

Figure 7 shows a plot of the percent change in value index per square foot of basal area, against the percent basal area removed and also indicates the ownership of the plot. Value index shows a pattern of increasing variability in value gained and lost as percent of basal area removed increases, just as value does. However, with value index, public plots tend to be above zero, the line at which stand value remains unchanged in a harvest, suggesting increases in stand value per square foot of basal area due to harvesting. While the density distribution of private plots tends to be at or below the line, suggesting no overall change in stand value per square foot of basal area. This is significant in that it suggests that although a value reduction occurs with harvest in both public and private plots, on public plots this value reduction is due mainly to removing larger trees; harvests on public plots tend to improve the species composition of the plot. On the other hand, harvests on private plots are just as likely to worsen the species composition of the plot as they are to improve it.

Figure 7 – Plot percent change in value index per ft^2 of basal area versus percent of basal area removed, 20% to 85% basal area removed natural hardwood plots, by public and private

The graphical illustration in Figure 7 is confirmed by the results in Table 12 that show that the average percent change in value index per ft^2 of basal area for private plots was -0.3%, not significantly different from zero. The average percent change in value index per ft^2 of basal area for public plots was 8.4% and was significantly different from zero. Furthermore, this value is significantly different from the average percent change in value index per ft^2 of basal area for private plots.

It does appear, however, that the reduction in value per ft^2 of basal area shown in Figure 6 is largely due to a tendency to harvest larger trees rather than smaller trees, on both public and private plots. This tendency can be assessed by calculating the ratio of average diameter harvested over the average stand diameter prior to harvest. This statistic is shown in Figure 8 where it is graphed against the percent value change per square foot of basal area. Plots that are graphed in the upper-left quadrant of Figure 8, have experienced a harvest with a negative change in value per ft^2 and a harvest-diameter to average-diameter ratio greater than 1. They show two harvest behaviors: 1) the stand value density is reduced (i.e., higher-value species are more likely to be harvested than lower-value species), and 2) average stand diameter is reduced (i.e., larger trees are more likely to be selected for harvest than smaller trees). These harvests tend to take large, valuable trees, and leave smaller, less valuable trees. Conversely, plots in the lower right quadrant, with a positive change in value per ft^2 and a harvest diameter-average diameter ratio less than 1 tend to be harvests that remove smaller trees from the stand and leave bigger trees, and also tend to leave higher-value species in the residual stand.

Figure 8 shows a large number of private harvest observations in the upper-left part of the graph. Public harvest observations, on the other hand, tend to group near 1 with respect to the ratio of tree diameter removed, with relatively few observations on the negative side of the value change axis. In this chart, the difference between harvest activity on private and public stands is more obvious.

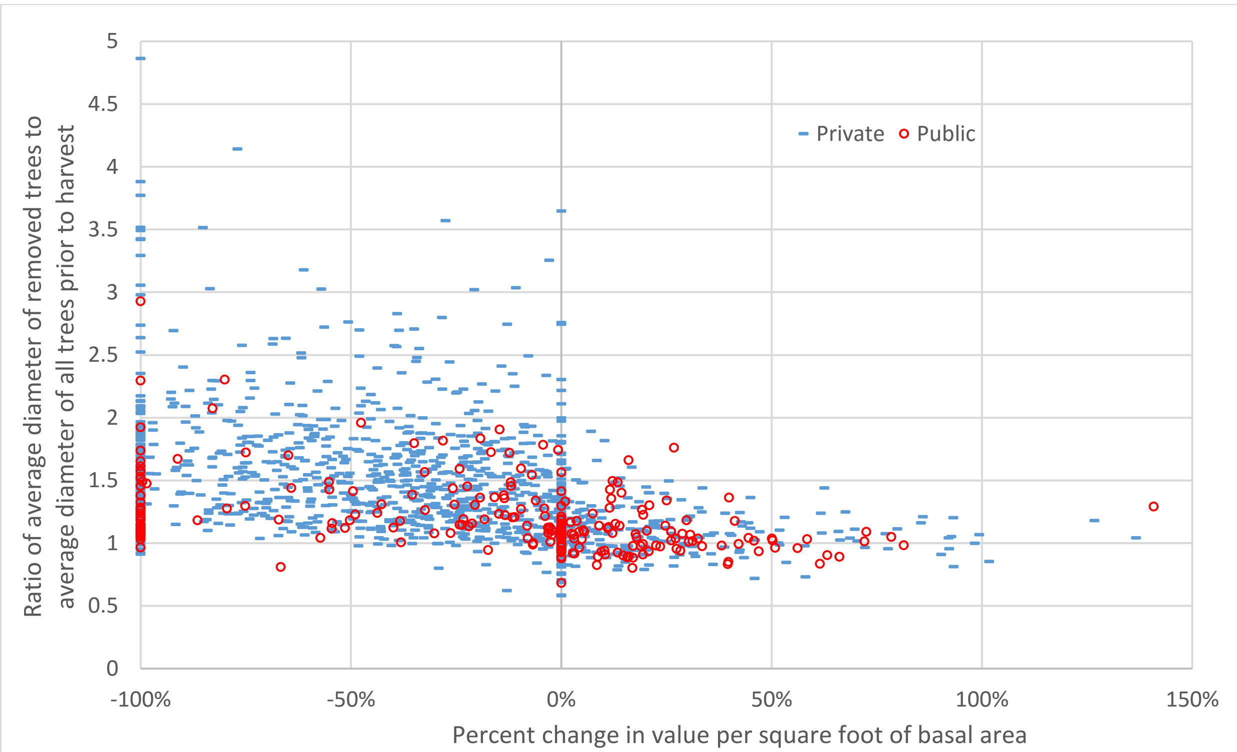

Figure 8 – Plots by percent change in value per ft2 of basal area, by average diameter removed, for natural hardwood plots between 20% to 85% basal area removed, with separate private and public groupings.

A Welch two-sample t-test was run between private and public plots for the three stand metrics, in addition to a one sample t-test of whether the mean percent change in value per square foot of basal area is significantly different from zero, and whether the ratio of diameter harvested to average plot diameter is significantly different from one.

Table 12 - Analysis of mean % change in value index per foot squared basal area, % change in value per foot squared basal area, and mean ratio of average diameter harvested to initial average stand diameter by ownership, with significant difference from 0 and 1.

		% Change Value per Foot^2 BA	% Change Value Index per Foot^2 BA	Ratio of average diameter harvested to initial average stand diameter
Private n=1244	95% CI Upper	-33.1%	1.00%	1.47
	Mean	-35.6%	-0.30%	1.45
	95% CI Lower	-38.1%	-1.50%	1.42
Sig Mean	*P-Value*	*(not 0) 0*	*(not 0) 0.653*	*(not 1) 0*
			(Different from 0)	*(Different from 1)*
Public n=240	95% CI Upper	-11.8%	11.60%	1.25
	Mean	-18.0%	8.40%	1.21
	95% CI Lower	-24.2%	5.10%	1.17
Sig Mean	*P-Value*	*(not 0) 0*	*(not 0) 0*	*(not 1) 0*
Sig Owner Difference	*P-Value*	*0*	*0*	*0*

The result as shown in table 12 was a significant difference between public and private ownerships for percent change in value per square foot of BA, also for percent change in value index per square foot of basal area, as well as the ratio of average diameter of harvested trees to average plot diameter prior to harvest, thus we were able to reject the null that there is no difference between public and private harvest behavior regarding these three metrics.

In addition, the results show a higher basal area volume harvested, but a significantly positive net increase in value for public harvests, versus no significant change in value for private harvests. The mean ratio of the diameter of harvested trees to initial stand diameter was substantially higher in private stands than in pubic stands, and both were significantly greater than 1. Therefore, public harvests in the 20% to 85% category remove more basal area overall, but tend to improve the value of the stand in the process, while harvesting larger than average, but significantly smaller trees than their private counterparts. For example, a 12” average diameter plot would equal an average harvested diameter of 17.4” on a private stand, and an average harvested diameter of 14.5” on a public stand, with a significantly different mean harvested diameter between the two.

Chapter 5 - Conclusion

The work on this project has been the culmination of a multiple-year project funded by APHIS. The project has involved collecting and consolidating the price data from the 22-state region of interest and creating a system of MS ACCESS queries from to extract the needed data from each state's FIA database. Further creating and refining a working FIA database product from 22 separate states, to a dataset that could undergo uniform statistical assessment, was a considerable undertaking.

There were two major goals of this project. The first to better understand the factors influencing timber harvesting decisions in the northeastern United States. We accomplished this by using logistic models to determine the influence of key variables from the FIA data and other sources on the probability of three types of harvest. To that end, the results were consistent with expectations, and the trends displayed made sense silviculturally. One would expect that diameter and other volumetric indicators would influence harvest probability at both the plot and individual tree level, and they did. Discovering that value was significant at the plot level, but not statistically significant at the tree level was unexpected, but assuming that stand harvest decisions are separate from tree harvesting decisions, one could expect there to be differences in motivation at each level.

One contribution of this research was the separate analysis of different types of harvests based on the proportion of the basal area that was removed. Harvests were divided into 1) light thinnings (less than 20% of the basal area (BA) removed), 2) medium-heavy thinnings (between 20 and 85% of the BA removed), and 3) stand-replacing harvests (more than 85% of the BA removed). The rationale for this approach was that the motivations for different harvests are likely different, so the predictive models for the different types of harvests should be different. Multinomial logistic models were used at the plot level to estimate the probability of one of the three types of harvest or of no harvest. Independent logistic models were used for each type of harvest (and for each modeling category and ownership) to estimate the probability of a given tree being harvested. The model coefficients varied for different types of harvests, supporting our assumption that factors influencing a harvest are different depending on the basal area removal rate. In other words, people's motivations change based on their goal in performing a harvest.

This information will help foresters and ecologists better understand the management decisions of landowners.

Comparing the management decisions of public versus private forest own is also important. Privately held land is managed differently than publicly held land because public objectives are often different than private objectives. This research found that public forests undergo poorly executed harvesting practices less often, as evidenced by stand value and size reductions. Public lands were much less likely to undergo a harvest at all. Furthermore, cull trees were much more likely to be harvested on public land versus private, as you would expect if the management objective was to improve a stand rather than simply harvest valuable standing timber.

The second goal of our project was much less clearly satisfied. We wanted to create models with strong harvest prediction ability. Although McFadden R^2 values are more appropriate for model building than interpretation (Hosmer Jr et al., 2013), plot model R^2 values indicate that plot models poorly fit our model data. Tree model R^2 were significantly better overall. The other issue in model building is simply data sparsity. Although the dataset is quite large, using so many separate models to correctly differentiate between significant variables according to harvest volume, species, and stand origin in each modeling dataset, causes limited data in each category as the overall number of harvests is under 10%. An increased amount of observations may help to produce better overall predictive models, as well as utilizing more variables in the model.

Overall Outcomes

Site factors tend to be non-significant for predicting high intensity harvests. For these types of harvests, site factors were not as strongly significant in both public and private models. This is a function of data sparsity in these model categories, but also likely due to economic and environmental factors, such as the need for immediate income, invasive species damage, and market recession, many of which have been studied as influencing harvest activity (Binkley, 1981; Butler and Leatherberry, 2004; Gong et al., 2005; Joshi and Arano, 2009b; Straka et al., 1984). Variables related to operability and accessibility tend to be important for predicting lower-volume harvests.

Diameter is significantly positively correlated with harvests in nearly all cases. However, $diameter^2$ is significantly negatively related to the probability of harvest. This leads us to conclude that the probability of harvest reaches a maximum at some diameter, after which the harvest probability decreases. This raises an interesting possibility, which has been cited in literature regarding ownership information from the timber woodland owner's survey, that woodlots exist as recreational or conservation forests, continuously preserved without the intention of ever being harvested (Butler and Leatherberry 2004). The strong significance of this nonlinear response seems to support that hypothesis. Assessing diameter further by looking at size, private landowners harvest natural hardwood stands with progressively greater probability as volume and diameter increase, but with a significant diameter squared term, this harvest probability reaches a maximum.

Interestingly, tree price was included in the tree models, but was ultimately dropped from consideration for general lack of significance, and also the fact that species tended to explain variation in harvests more consistently. In the plot-level models, however, value per $foot^2$ of basal area was significantly positively related to probability of harvest in many cases. This suggests that value is a driving factor of harvests at the plot level, but not at the tree level. Decision making that involves total plot value as a determinant in the harvesting consideration process is carried out at the plot level, perhaps in the form of a timber cruise, but absent from the tree level. Gong et al (1998) and Prestemon and Wear (2000) also concluded that price was a significant factor in harvest probability.

In calculating the value and size removed from the stand at harvest, the significance of finding that value per square foot of basal area is reduced in both public and private harvests, while value index, a measure of all tree value, is improved in public harvests while unchanged in private harvests cannot be overstated. Both owners decrease the value density of their stands when harvesting, but when smaller trees are also considered, as would be in improvement cuts, value is improved in public stands, while it is unchanged in private stands. This suggests what when all size classes of trees are considered in terms of value, public harvesting is improving future stand value while private harvesting is not.

Future Considerations

The work carried out in this thesis was an exploration of harvesting behavior using the first completed second cycle of FIA data. Because most FIA data has only now just finished the second sampling cycle in many states, a third sampling cycle of data would help to reinforce observed patterns in harvest mentality and behavior. Future research that assess the third full cycle of plot observations would add significantly to validating these results.

In addition, even with such a large study area as the 22 northeastern states examined in this work, lack of data was still an issue. Division into basal area harvested categories, separation of public and private landowners, and assessment of multiple species/forest types resulted in data sparsity in some data categories. This meant division of the dataset would be difficult beyond the level done in this research.

Although there was strong significance given the variables used in this assessment, model predictive ability was weak. As a result, the possible inclusion of The US Forest Services Woodland Owners Survey could add to model prediction power. This dataset is only available for a limited number of plots, however, so data sparsity would be an even greater issue, but the introduction of more socio-economic variables could strengthen the predictive ability of the harvesting models developed in this study.

Appendix

Table A1 - Project state list, with corresponding region, price grouping, and listing of cycle 1 and cycle 2 year ranges.

State	Region	Price Group	Cycle 1 Years	Cycle 2 Years
Connecticut	CT/MA/RI/VT/NH	CT/MA/RI	2003-2007	2007-2012
Delaware	MD/DE/NJ	DE/MD/VA/WV	2004-2008	2008-2013
Illinois	IA/IL/IN	IL/IN	2003-2007	2007-2012
Indiana	IA/IL/IN	IL/IN	2003-2007	2007-2012
Iowa	IA/IL/IN	IA/MN/MO	2003-2007	2007-2012
Kentucky	Kentucky	KY/OH	2003-2007	2003-2007
Maine	Maine	Maine	2003-2007	2007-2012
Maryland	MD/DE/NJ	DE/MD/VA/WV	2004-2008	2008-2013
Massachusetts	CT/MA/RI/VT/NH	CT/MA/RI	2003-2007	2007-2012
Michigan	Michigan	MI/WI	2003-2007	2007-2012
Minnesota	Minnesota	IA/MN/MO	2003-2007	2007-2012
Missouri	Missouri	IA/MN/MO	2003-2007	2007-2012
New Hampshire	CT/MA/RI/VT/NH	NH/VT	2003-2007	2007-2012
New Jersey	MD/DE/NJ	NJ/PA	2004-2008	2008-2013
New York	New York	New York	2003-2007	2007-2012
Ohio	Ohio	KY/OH	2003-2007	2007-2012
Pennsylvania	Pennsylvania	NJ/PA	2003-2007	2007-2012
Rhode Island	CT/MA/RI/VT/NH	CT/MA/RI	2003-2007	2007-2012
Vermont	CT/MA/RI/VT/NH	NH/VT	2003-2007	2007-2012
Virginia	Virginia	DE/MD/VA/WV	2003-2008	2007-2013
West Virginia	West Virginia	DE/MD/VA/WV	2004-2008	2008-2013
Wisconsin	Wisconsin	MI/WI	2003-2007	2007-2012

Table A2 - Species Price Grouping by Regionlisting of all FIA species with corresponding price region used to value assessment.

Price Region	Species Name	Price Region	Species Name	Price Region	Species Name	Price Region	Species Name
CT/MA/RI	ash	IA/MN/MO	Other Hardwoods	Maine	Spruce-Fir	New York	Misc Hardwoods
CT/MA/RI	beech	IA/MN/MO	Red & White Pine	Maine	Sugar Maple	New York	NCS
CT/MA/RI	blackbirch	IA/MN/MO	Spruce	Maine	White Birch	New York	Oak, Chestnut
CT/MA/RI	cherry	IA/MN/MO	Tamarack	Maine	White Pine	New York	Oak, Red
CT/MA/RI	hemlock	IA/MN/MO	White Cedar	Maine	Yellow Birch	New York	Oak, White
CT/MA/RI	NCS	IL/IN	Basswood	MI/WI	ASH	New York	Pine, Red
CT/MA/RI	otherhdwd	IL/IN	Beech	MI/WI	ASPEN	New York	Pine, White
CT/MA/RI	otheroaks	IL/IN	Black oak	MI/WI	BASSWOOD	New York	Spruce (spp.)
CT/MA/RI	othersfwd	IL/IN	Black walnut	MI/WI	BEECH	New York	Tulip Poplar
CT/MA/RI	pallethdwd	IL/IN	Cedar	MI/WI	BIRCH WHITE	New York	Walnut, Black
CT/MA/RI	paperbirch	IL/IN	Cherry	MI/WI	BIRCH YELLOW	NH/VT	ash
CT/MA/RI	poplar	IL/IN	Cottonwood	MI/WI	CEDAR - WHITE	NH/VT	aspen
CT/MA/RI	redmaple	IL/IN	Elm	MI/WI	CHERRY	NH/VT	basswood
CT/MA/RI	redoak	IL/IN	Hard maple	MI/WI	COTTONWOOD	NH/VT	beech
CT/MA/RI	redpine	IL/IN	NCS	MI/WI	ELM	NH/VT	butternut
CT/MA/RI	spruce	IL/IN	Pine	MI/WI	FIR - BALSAM	NH/VT	cedar
CT/MA/RI	sugarmaple	IL/IN	Red oak	MI/WI	HEMLOCK	NH/VT	cherry
CT/MA/RI	whiteoak	IL/IN	S. Hickory	MI/WI	HICKORY	NH/VT	elm
CT/MA/RI	whitepine	IL/IN	Soft maple	MI/WI	MAPLE OTHER	NH/VT	hemlock
CT/MA/RI	yellowbirch	IL/IN	Sweetgum	MI/WI	MAPLE SUGAR	NH/VT	NCS
DE/MD/VA/WV	Ash	IL/IN	Sycamore	MI/WI	MISC. HARDWOODS	NH/VT	other hdwd
DE/MD/VA/WV	Black Cherry	IL/IN	Tulip poplar	MI/WI	NCS	NH/VT	red maple
DE/MD/VA/WV	Hard Maple	IL/IN	White ash	MI/WI	OAK OTHER	NH/VT	red oak
DE/MD/VA/WV	Hemlock	IL/IN	White oak	MI/WI	OAK RED	NH/VT	red pine
DE/MD/VA/WV	Hickory	KY/OH	Ash	MI/WI	OAK WHITE	NH/VT	spruce/fir
DE/MD/VA/WV	Misc Hdwd	KY/OH	Basswood	MI/WI	PINE JACK	NH/VT	sugar maple
DE/MD/VA/WV	Mixed Oak	KY/OH	Cherry	MI/WI	PINE RED	NH/VT	tamarack
DE/MD/VA/WV	NCS	KY/OH	Hard Maple	MI/WI	PINE WHITE	NH/VT	white birch
DE/MD/VA/WV	Pine	KY/OH	Hickory	MI/WI	RED MAPLE	NH/VT	white oak
DE/MD/VA/WV	Red/Black Oak	KY/OH	NCS	MI/WI	TAMARACK	NH/VT	white pine
DE/MD/VA/WV	Soft Maple	KY/OH	Pine	MI/WI	WALNUT	NH/VT	yellow birch

Price Region	Species Name	Price Region	Species Name	Price Region	Species Name	Price Region	Species Name
DE/MD/VA /WV	Walnut	KY/OH	Red Oak	MI/WI	WHITE SPRUCE	NJ/PA	Black Cherry
DE/MD/VA /WV	White Oak	KY/OH	Soft Maple	New York	Ash, White	NJ/PA	Hard Maple
DE/MD/VA /WV	Yellow Poplar	KY/OH	Walnut	New York	Aspen	NJ/PA	Hemlock
IA/MN/MO	Ash	KY/OH	White Oak	New York	Basswood	NJ/PA	Misc. Hardwoods
IA/MN/MO	Aspen	KY/OH	Yellow Poplar	New York	Beech	NJ/PA	Mixed Oak
IA/MN/MO	Balm of Gilead	Maine	Ash	New York	Birch, White	NJ/PA	NCS
IA/MN/MO	Balsam Fir	Maine	Aspen	New York	Birch, Yellow	NJ/PA	Northern Red Oak
IA/MN/MO	Basswood	Maine	Beech	New York	Butternut	NJ/PA	Soft Maple
IA/MN/MO	Birch	Maine	Cedar	New York	Cherry, Black	NJ/PA	White Ash
IA/MN/MO	Elm	Maine	Hemlock	New York	Elm, American	NJ/PA	White Oak
IA/MN/MO	Jack Pine	Maine	NCS	New York	Hemlock	NJ/PA	White Pine
IA/MN/MO	Maple	Maine	Oak	New York	Hickory (spp.)	NJ/PA	Yellow Poplar
IA/MN/MO	NCS	Maine	Red Pine	New York	Maple, Red (Soft)		
IA/MN/MO	Oak	Maine	Soft Maple	New York	Maple, Sugar (Hard)		

Table A3 - FIA species and their common harvest species grouping category used for tree model species categorical variables.

SPCD	COMMON_NAME	Harvest Species Name	SPCD	COMMON_NAME	Harvest Species Name
10	Fir Spp.	Spruce-Fir	600	Walnut Spp.	Other Valuable Hardwood
12	Balsam Fir	Spruce-Fir	601	Butternut	Other Valuable Hardwood
15	White Fir	Spruce-Fir	602	Black Walnut	Other Valuable Hardwood
16	Fraser Fir	Spruce-Fir	611	Sweetgum	Misc Hardwoods
43	Atlantic White-Cedar	Other Softwoods	621	Yellow-Poplar	Yellow-Poplar
57	Redcedar/Juniper Spp.	Other Softwoods	641	Osage-Orange	Non-Commercial
68	Eastern Redcedar	Non-Canopy	650	Magnolia Spp.	Misc Hardwoods
70	Larch Spp.	Other Softwoods	651	Cucumbertree	Misc Hardwoods
71	Tamarack (Native)	Other Softwoods	652	Southern Magnolia	Misc Hardwoods
90	Spruce Spp.	Spruce-Fir	653	Sweetbay	Misc Hardwoods
91	Norway Spruce	Spruce-Fir	654	Bigleaf Magnolia	Misc Hardwoods
93	Engelmann Spruce	Spruce-Fir	655	Mountain Or Fraser Magnolia	Non-Commercial
94	White Spruce	Spruce-Fir	658	Umbrella Magnolia	Non-Commercial
95	Black Spruce	Spruce-Fir	660	Apple Spp.	Non-Canopy
96	Blue Spruce	Spruce-Fir	661	Oregon Crab Apple	Non-Canopy
97	Red Spruce	Spruce-Fir	662	Southern Crab Apple	Non-Canopy
100	Pine Spp.	Other Softwoods	663	Sweet Crab Apple	Non-Canopy
105	Jack Pine	Southern-Jack Pine	664	Prairie Crab Apple	Non-Canopy
110	Shortleaf Pine	Southern-Jack Pine	680	Mulberry Spp.	Non-Commercial
122	Ponderosa Pine	Other Softwoods	681	White Mulberry	Non-Commercial
123	Table Mountain Pine	Southern-Jack Pine	682	Red Mulberry	Non-Commercial
125	Red Pine	Red & White Pine	691	Water Tupelo	Misc Hardwoods
126	Pitch Pine	Southern-Jack Pine	693	Blackgum	Misc Hardwoods
128	Pond Pine	Southern-Jack Pine	694	Swamp Tupelo	Misc Hardwoods
129	Eastern White Pine	Red & White Pine	701	Eastern Hophornbeam	Non-Canopy
130	Scotch Pine	Southern-Jack Pine	711	Sourwood	Misc Hardwoods
131	Loblolly Pine	Southern-Jack Pine	712	Paulownia, Empress-Tree	Misc Hardwoods
132	Virginia Pine	Southern-Jack Pine	721	Redbay	Non-Canopy
136	Austrian Pine	Southern-Jack Pine	722	Water-Elm, Planertree	Non-Commercial
202	Douglas-Fir	Other Softwoods	729	Sycamore Spp.	Misc Hardwoods
221	Baldcypress	Other Softwoods	731	American Sycamore	Misc Hardwoods
222	Pondcypress	Other Softwoods	740	Cottonwood And Poplar Spp.	Aspen
241	Northern White-Cedar	Other Softwoods	741	Balsam Poplar	Aspen
260	Hemlock Spp.	Other Softwoods	742	Eastern Cottonwood	Aspen
261	Eastern Hemlock	Other Softwoods	743	Bigtooth Aspen	Aspen
262	Carolina Hemlock	Other Softwoods	744	Swamp Cottonwood	Aspen
299	Unknown Dead Conifer	Unknown	746	Quaking Aspen	Aspen
310	Maple Spp.	Other Maple	752	Silver Poplar	Aspen
311	Florida Maple	Other Maple	753	Lombardy Poplar	Aspen
313	Boxelder	Misc Hardwoods	760	Cherry And Plum Spp.	Non-Commercial
314	Black Maple	Other Maple	761	Pin Cherry	Non-Canopy
315	Striped Maple	Non-Canopy	762	Black Cherry	Other Valuable Hardwood
316	Red Maple	Red Maple	763	Chokecherry	Non-Canopy
317	Silver Maple	Other Maple	764	Peach	Non-Canopy

318	Sugar Maple	Sugar Maple	765	Canada Plum	Non-Canopy
319	Mountain Maple	Non-Canopy	766	American Plum	Non-Canopy
320	Norway Maple	Other Maple	771	Sweet Cherry, Domesticated	Non-Canopy
330	Buckeye, Horsechestnut Spp.	Misc Hardwoods	772	Sour Cherry, Domesticated	Non-Canopy
331	Ohio Buckeye	Misc Hardwoods	800	Oak Spp.	Other White Oak
332	Yellow Buckeye	Misc Hardwoods	800	Oak Spp	Other White Oak
341	Ailanthus	Non-Commercial	802	White Oak	White Oak
345	Mimosa, Silktree	Non-Canopy	804	Swamp White Oak	Other White Oak
355	European Alder	Non-Canopy	806	Scarlet Oak	Other Red Oak
356	Serviceberry Spp.	Misc Hardwoods	809	Northern Pin Oak	Valuable Red Oak
357	Common Serviceberry	Misc Hardwoods	812	Southern Red Oak	Valuable Red Oak
358	Roundleaf Serviceberry	Non-Commercial	813	Cherrybark Oak	Valuable Red Oak
367	Pawpaw	Non-Canopy	816	Scrub Oak	Non-Commercial
370	Birch Spp.	Birch	817	Shingle Oak	Valuable Red Oak
371	Yellow Birch	Yellow Birch	819	Turkey Oak	Other Red Oak
372	Sweet Birch	Birch	820	Laurel Oak	Non-Commercial
373	River Birch	Birch	822	Overcup Oak	Other White Oak
375	Paper Birch	Birch	823	Bur Oak	Other White Oak
379	Gray Birch	Birch	824	Blackjack Oak	Other Red Oak
381	Chittamwood, Gum Bumelia	Misc Hardwoods	825	Swamp Chestnut Oak	Other White Oak
391	American Hornbeam, Musclewood	Non-Canopy	826	Chinkapin Oak	Other White Oak
400	Hickory Spp.	Hickories	827	Water Oak	Other Red Oak
401	Water Hickory	Hickories	828	Texas Red Oak	Other Red Oak
402	Bitternut Hickory	Hickories	830	Pin Oak	Valuable Red Oak
403	Pignut Hickory	Hickories	831	Willow Oak	Valuable Red Oak
404	Pecan	Other Valuable Hardwood	832	Chestnut Oak	Other White Oak
405	Shellbark Hickory	Hickories	833	Northern Red Oak	Valuable Red Oak
407	Shagbark Hickory	Hickories	834	Shumard Oak	Valuable Red Oak
408	Black Hickory	Hickories	835	Post Oak	Other White Oak
409	Mockernut Hickory	Hickories	837	Black Oak	Other Red Oak
410	Sand Hickory	Hickories	840	Dwarf Post Oak	Non-Commercial
412	Red Hickory	Hickories	845	Dwarf Chinkapin Oak	Non-Commercial
421	American Chestnut	Non-Commercial	901	Black Locust	Misc Hardwoods
422	Allegheny Chinkapin	Misc Hardwoods	920	Willow Spp.	Non-Commercial
424	Chinese Chestnut	Misc Hardwoods	921	Peachleaf Willow	Non-Commercial
450	Catalpa Spp.	Misc Hardwoods	922	Black Willow	Non-Commercial
451	Southern Catalpa	Misc Hardwoods	923	Bebb Willow	Non-Commercial
452	Northern Catalpa	Misc Hardwoods	926	Balsam Willow	Non-Canopy
460	Hackberry Spp.	Misc Hardwoods	927	White Willow	Non-Commercial
461	Sugarberry	Elm	929	Weeping Willow	Misc Hardwoods
462	Hackberry	Misc Hardwoods	931	Sassafras	Non-Canopy
471	Eastern Redbud	Non-Canopy	934	Mountain-Ash Spp.	Non-Commercial
481	Yellowwood	Non-Commercial	935	American Mountain-Ash	Non-Canopy
491	Flowering Dogwood	Non-Canopy	936	European Mountain-Ash	Non-Canopy

500	Hawthorn Spp.	Non-Canopy
501	Cockspur Hawthorn	Non-Canopy
502	Downy Hawthorn	Non-Canopy
520	Persimmon Spp.	Misc Hardwoods
521	Common Persimmon	Misc Hardwoods
531	American Beech	American Beech
540	Ash Spp.	Ash
541	White Ash	Ash
543	Black Ash	Ash
544	Green Ash	Ash
545	Pumpkin Ash	Ash
546	Blue Ash	Ash
548	Carolina Ash	Ash
551	Waterlocust	Misc Hardwoods
552	Honeylocust	Misc Hardwoods
561	Ginkgo, Maidenhair Tree	Non-Commercial
571	Kentucky Coffeetree	Misc Hardwoods
580	Silverbell Spp.	Non-Canopy
581	Carolina Silverbell	Non-Canopy
591	American Holly	Non-Canopy
937	Northern Mountain-Ash	Non-Commercial
950	Basswood Spp.	Misc Hardwoods
951	American Basswood	Misc Hardwoods
952	White Basswood	Misc Hardwoods
970	Elm Spp.	Elm
971	Winged Elm	Elm
972	American Elm	Elm
974	Siberian Elm	Elm
975	Slippery Elm	Elm
976	September Elm	Elm
977	Rock Elm	Elm
993	Chinaberry	Non-Commercial
997	Russian-Olive	Non-Canopy
998	Unknown Dead Hardwood	Unknown
999	Other Or Unknown Live Tree	Unknown

Table A4 - FIA Forest Types to Combined Forest Type Groups used in models and their respective forest type groupings used for modeling forest type in plot models.

Forest Type Codes		
FORTYPCD	**Forest Type**	**Type Group**
100	White/Red/Jack Pine Group	Northern Pines - Hemlock
101	Jack Pine	Northern Pines - Hemlock
102	Red Pine	Northern Pines - Hemlock
103	Eastern White Pine	Northern Pines - Hemlock
104	Eastern White Pine/Eastern Hemlock	Northern Pines - Hemlock
105	Eastern Hemlock	Northern Pines - Hemlock
120	Spruce/Fir Group	Spruce - Fir
121	Balsam Fir	Spruce - Fir
122	White Spruce	Spruce - Fir
123	Red Spruce	Spruce - Fir
124	Red Spruce/Balsam Fir	Spruce - Fir
125	Black Spruce	Spruce - Fir
126	Tamarack	Spruce - Fir
127	Northern White-Cedar	Spruce - Fir
128	Fraser Fir	Spruce - Fir
129	Red Spruce/Fraser Fir	Spruce - Fir
140	Longleaf/Slash Pine Group	Southern Pines - Other Conifers
141	Logleaf Pine	Southern Pines - Other Conifers
142	Slash Pine	Southern Pines - Other Conifers
150	Tropical Softwoods Group	Southern Pines - Other Conifers
151	Tropical Pines	Southern Pines - Other Conifers
160	Loblolly/Shortleaf Pine Group	Southern Pines - Other Conifers
161	Loblolly Pine	Southern Pines - Other Conifers
162	Shortleaf Pine	Southern Pines - Other Conifers
163	Virginia Pine	Southern Pines - Other Conifers
164	Sand Pine	Southern Pines - Other Conifers
165	Table Mountain Pine	Southern Pines - Other Conifers
166	Pond Pine	Southern Pines - Other Conifers
167	Pitch Pine	Southern Pines - Other Conifers
168	Spruce Pine	Southern Pines - Other Conifers
170	Other Eastern Softwoods Group	Southern Pines - Other Conifers
171	Eastern Redcedar	Southern Pines - Other Conifers
172	Florida Softwoods	Southern Pines - Other Conifers
180	Pinyon/Juniper Group	Southern Pines - Other Conifers
182	Rocky Mountain Juniper	Southern Pines - Other Conifers

Forest Type Codes		
FORTYPCD	**Forest Type**	**Type Group**
184	Juniper Woodland	Southern Pines - Other Conifers
185	Pinyon/Juniper Woodland	Southern Pines - Other Conifers
200	Douglas-Fir Group	Southern Pines - Other Conifers
201	Douglas-Fir	Southern Pines - Other Conifers
202	Port-Orford-Cedar	Southern Pines - Other Conifers
203	Bigcone Douglas-Fir	Southern Pines - Other Conifers
220	Ponderosa Pine Group	Southern Pines - Other Conifers
221	Ponderosa Pine	Southern Pines - Other Conifers
222	Incense-Cedar	Southern Pines - Other Conifers
224	Sugar Pine	Southern Pines - Other Conifers
225	Jeffrey Pine	Southern Pines - Other Conifers
226	Coulter Pine	Southern Pines - Other Conifers
240	Western White Pine Group	Southern Pines - Other Conifers
241	Western White Pine	Southern Pines - Other Conifers
260	Fir/Spruce/Mountain Hemlock Group	Southern Pines - Other Conifers
261	White Fir	Southern Pines - Other Conifers
262	Red Fir	Southern Pines - Other Conifers
263	Noble Fir	Southern Pines - Other Conifers
264	Pacific Silver Fir	Southern Pines - Other Conifers
265	Engelmann Spruce	Southern Pines - Other Conifers
266	Engelmann Spruce/Subalpine Fir	Southern Pines - Other Conifers
267	Grand Fir	Southern Pines - Other Conifers
268	Subalpine Fir	Southern Pines - Other Conifers
269	Blue Spruce	Southern Pines - Other Conifers
270	Mountain Hemlock	Southern Pines - Other Conifers
271	Alaska-Yellow-Cedar	Southern Pines - Other Conifers
280	Lodgepole Pine Group	Southern Pines - Other Conifers
281	Lodgepole Pine	Southern Pines - Other Conifers
300	Hemlock/Sitka Spruce Group	Southern Pines - Other Conifers
301	Western Hemlock	Southern Pines - Other Conifers
304	Western Redcedar	Southern Pines - Other Conifers
305	Sitka Spruce	Southern Pines - Other Conifers
320	Western Larch Group	Southern Pines - Other Conifers
321	Western Larch	Southern Pines - Other Conifers
340	Redwood Group	Southern Pines - Other Conifers
341	Redwood	Southern Pines - Other Conifers
342	Giant Sequoia	Southern Pines - Other Conifers

Forest Type Codes		
FORTYPCD	**Forest Type**	**Type Group**
360	Other Western Softwoods Group	Southern Pines - Other Conifers
361	Knobcone Pine	Southern Pines - Other Conifers
362	Southwestern White Pine	Southern Pines - Other Conifers
363	Bishop Pine	Southern Pines - Other Conifers
364	Monterey Pine	Southern Pines - Other Conifers
365	Foxtail Pine/Bristlecone Pine	Southern Pines - Other Conifers
366	Limber Pine	Southern Pines - Other Conifers
367	Whitebark Pine	Southern Pines - Other Conifers
368	Miscellaneous Western Softwoods	Southern Pines - Other Conifers
369	Western Juniper	Southern Pines - Other Conifers
370	California Mixed Conifer Group	Southern Pines - Other Conifers
371	California Mixed Conifer	Southern Pines - Other Conifers
380	Exotic Softwoods Group	Southern Pines - Other Conifers
381	Scotch Pine	Southern Pines - Other Conifers
383	Other Exotic Softwoods	Southern Pines - Other Conifers
384	Norway Spruce	Southern Pines - Other Conifers
385	Introduced Larch	Southern Pines - Other Conifers
390	Other Softwoods Group	Southern Pines - Other Conifers
391	Other Softwoods	Southern Pines - Other Conifers
400	Oak/Pine Group	Oak - Pine
401	Eastern White Pine/Northern Red Oak/White Ash	Oak - Pine
402	Eastern Redcedar/Hardwood	Oak - Pine
403	Longleaf Pine/Oak	Oak - Pine
404	Shortleaf Pine/Oak	Oak - Pine
405	Virginia Pine/Southern Red Oak	Oak - Pine
406	Loblolly Pine/Hardwood	Oak - Pine
407	Slash Pine/Hardwood	Oak - Pine
409	Other Pine/Hardwood	Oak - Pine
500	Oak/Hickory Group	Oak - Hickory
501	Post Oak/Blackjack Oak	Oak - Hickory
502	Chestnut Oak	Oak - Hickory
503	White Oak/Red Oak/Hickory	Oak - Hickory
504	White Oak	Oak - Hickory
505	Notrthern Red Oak	Oak - Hickory
506	Yellow-Poplar/White Oak/Northern Red Oak	Oak - Hickory
507	Sassafras/Persimmon	Oak - Hickory
508	Sweetgum/Yellow-Poplar	Oak - Hickory

Forest Type Codes		
FORTYPCD	**Forest Type**	**Type Group**
509	Bur Oak	Oak - Hickory
510	Scarlet Oak	Oak - Hickory
511	Yellow-Poplar	Oak - Hickory
512	Black Walnut	Oak - Hickory
513	Black Locust	Oak - Hickory
514	Southern Scrub Oak	Oak - Hickory
515	Chestnut Oak/Black Oak/Scarlet Oak	Oak - Hickory
516	Cherry/White Ash/Yellow-Poplar	Oak - Hickory
517	Elm/Ash/Black Locust	Oak - Hickory
519	Red Maple/Oak	Oak - Hickory
520	Mixed Upland Hardwoods	Oak - Hickory
600	Oak/Gum/Cypress Group	Swamp Forests
601	Swamp Chestnut Oak/Cherrybark Oak	Swamp Forests
602	Sweetgum/Nuttall Oak/Willow Oak	Swamp Forests
605	Overcup Oak/Water Hickory	Swamp Forests
606	Atlantic White-Cedar	Swamp Forests
607	Baldcypress/Water Tupelo	Swamp Forests
608	Sweetbay/Swamp Tupelo/Red Maple	Swamp Forests
609	Baldcypress/Pondcypress	Swamp Forests
700	Elm/Ash/Cottonwood Group	Swamp Forests
701	Black Ash/American Elm/Red Maple	Swamp Forests
702	River Birch/Sycamore	Swamp Forests
703	Cottonwood	Swamp Forests
704	Willow	Swamp Forests
705	Sycamore/Pecan/American Elm	Swamp Forests
706	Sugarberry/Hackberry/Elm/Green Ash	Swamp Forests
707	Silver Maple/American Elm	Swamp Forests
708	Red Maple/Lowland	Swamp Forests
709	Cottonwood/Willow	Swamp Forests
722	Oregon Ash	Other Hardwoods
800	Maple/Beech/Birch Group	Northern Hardwood
801	Sugar Maple/Beech/Yellow Birch	Northern Hardwood
802	Black Cherry	Northern Hardwood
805	Hard Maple/Basswood	Northern Hardwood
809	Red Maple/Upland	Northern Hardwood
900	Aspen/Birch Group	Aspen - Birch
901	Aspen	Aspen - Birch

Forest Type Codes		
FORTYPCD	**Forest Type**	**Type Group**
902	Paper Birch	Aspen - Birch
903	Gray Birch	Aspen - Birch
904	Balsam Poplar	Aspen - Birch
905	Pin Cherry	Aspen - Birch
910	Alder/Maple Group	Other Hardwoods
911	Red Alder	Other Hardwoods
912	Bigleaf Maple	Other Hardwoods
920	Western Oak Group	Other Hardwoods
921	Gray Pine	Other Hardwoods
922	California Black Oak	Other Hardwoods
923	Oregon White Oak	Other Hardwoods
924	Blue Oak	Other Hardwoods
931	Coast Live Oak	Other Hardwoods
933	Canyon Live Oak	Other Hardwoods
934	Interior Live Oak	Other Hardwoods
935	California White Oak (Valley Oak)	Other Hardwoods
940	Tanoak/Laurel Group	Other Hardwoods
941	Tanoak	Other Hardwoods
942	California Laurel	Other Hardwoods
943	Giant Chinkapin	Other Hardwoods
960	Other Hardwoods Group	Other Hardwoods
961	Pacific Madrone	Other Hardwoods
962	Othe Hardwoods	Other Hardwoods
970	Woodland Hardwoods Group	Other Hardwoods
971	Deciduous Oak Woodland	Other Hardwoods
972	Evergreen Oak Woodland	Other Hardwoods
973	Mesquite Woodland	Other Hardwoods
974	Cercocarpus (Mountain Brush) Woodland	Other Hardwoods
975	Intermountain Maple Woodland	Other Hardwoods
976	Miscellaneous Woodland Hardwoods	Other Hardwoods
980	TropicalHardwoods Group	Other Hardwoods
982	Mangrove	Other Hardwoods
983	Palms	Other Hardwoods
984	Dry Forest	Other Hardwoods
985	Moist Forest	Other Hardwoods
986	Wet and Rain Forest	Other Hardwoods
987	Lower Montaine Wet and Rain Forest	Other Hardwoods

Forest Type Codes		
FORTYPCD	Forest Type	Type Group
989	Other Tropical Hardwoods	Other Hardwoods
990	Exotic Hardwoods Group	Other Hardwoods
991	Paulownia	Other Hardwoods
992	Melaleuca	Other Hardwoods
993	Eucalyptus	Other Hardwoods
995	Other Exotic Hardwoods	Other Hardwoods
999	Nonstocked	Nonstocked

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