EXAMINING THE POTENTIAL OF LANDSAT IMAGERY FOR THE ESTIMATION OF FOREST STAND-LEVEL STRUCTURES AND AN ANALYSIS OF PINE STUMPAGE PRICES BASED ON TIMBER SALE CHARACTERISTICS

by

HOJUNG KIM

(Under the direction of Chris Cieszewski)

ABSTRACT

Landsat imagery has been used for the estimation of forest stand-level characteristics with various techniques. We reviewed peer-reviewed research that employed Landsat imagery for the purpose of estimating forest stand-level characteristics from 1995 to 2012. Particularly, we focused on the study areas, forest parameters examined and technologies of classification employed. We investigated the trends and changes in using Landsat imagery for the estimation of forest stand-level characteristics. In terms of forest stand-level characteristics that have been estimated, above ground biomass (AGB) was thoroughly researched, but forest stand height and crown closures were estimated less frequently. In techniques employed, various forms of regression analysis seem to be the most used method and k-nearest neighbor followed it, and the other techniques were not employed enough but increasingly used.

Given the proven abilities of Landsat imagery for the estimation of forest structural characteristics, we estimated forest structure in the State of Georgia. We estimated premature forest areas where the age is 15 or under 15 using Landsat satellite imagery in southeastern Georgia. For the estimation of premature forest areas in Georgia, we employed three technologies: maximum likelihood classification (MLC), regression analysis, and k-nearest neighbor (kNN). In terms of overall accuracy, MLC and kNN produced relatively high-level accuracy. The kappa coefficient shows consistent results with overall accuracy.

Additionally, to research the implicit value of sale characteristics on the change of stumpage price, we developed a regression model with various sale characteristics to have insight into the change of timber price. Based on Timber Mart-South data collected from 1998 to 2007 in 11 southern states, we adopted a hedonic pricing method for the association of stumpage price of pine sawtimber with timber sale characteristics. We found that the stumpage price of pine sawtimber is positively related to sale size, contract length, sealed bid offering, and the number of bidders. It is also found that the presence of above average or excellence in grade, market conditions, and logging conditions made huge positive impacts on the stumpage price of pine sawtimber.

INDEX WORDS: Forest stand variables, Forest stand-level characteristics, Landsat imagery, Premature forest areas, Stumpage price, Hedonic price method

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CHAPTER 1

INTRODUCTION

Remote sensing imagery has been used for forest planning intensively (Holmgren and Thuresson, 1998). Remote sensing using satellite imagery or aerial photos has brought us broad-scale forest landscape information and associated land cover maps. Especially for estimating forest stand-level conditions across broad landscapes remote sensing imagery has been used efficiently to provide valuable information regarding forest structures for ecologists or forest managers (Cohen et al., 1995). Stand-level forest structural variables can be used as indicators for forest stand characteristics and developmental stages and essential information regarding various aspects of forest management including timber inventory, harvest, and disturbance management (Franklin et al., 2003). For field inventories, the role of remote sensing imagery has been used for the estimation of forest stand-level variables over local or large-scale landscape forest areas. These stand-level forest estimates will make forest strategic planning easy in forest areas where field work for forest inventories require too much time and money. They also help us to resolve a variety of problems and controversies concerning forest conservation and management.

As one type of remote sensing data, Landsat satellite imagery has been used for forest management and research purposes. Landsat satellite imagery has been increasingly used to describe broad-scale landscape processes such as land use or disturbances and has become an essential source in applications including forest variables at the local and regional scale (Lu, 2006; Maselli et al., 2011). There were technological problems of linear gaps in Landsat 7 imagery caused by the scan line corrector's failure, and the operation of Landsat 5 imagery was stopped by the U.S. Geological Survey in November 2011. However, because Landsat imagery has the advantages in its cost and popularity, large support groups have joined the processing steps. In particular, Landsat satellite imagery helps describe structural conditions for stand-level forest areas and has a suitable spatial resolution (30 m x 30 m) for regional mapping (Mäkelä and Pekkarinen, 2004). A forest stand can be defined as a tree group which is homogeneous in both species composition and structural conditions. Stand-level characteristics in forest areas involve the amount of above ground biomass (AGB), the average age, the total volume of timber, the average tree height, the average tree diameter at breast height (DBH), the crown closure, and the density. The imagery makes strategic planning easier with such stand-level characteristics of forested area where forest inventories are not easily accessible (Holmgren et al., 1998). Simultaneously, it is important to understand the accuracy and the associated uncertainty in the estimation of forest-stand characteristics. In chapter 2, we present a literature review which analyzes and summarizes peer-reviewed research regarding the estimation of stand-level forest characteristics using Landsat imagery from 1995 to 2012. In doing so, we examine the advantages and disadvantages of using Landsat imagery, and describe the challenges and gaps that should be addressed in future research. We evaluate the suitability for forest parameters estimated, the techniques employed, and auxiliary data used, and we analyze the current trends in the use of Landsat imagery to estimate forest stand-level characteristics. This analysis also helps us identify gaps in science.

Stand- level forest structural information is important in Earth conservation issues and forest management. We can define stands in terms of vegetative characteristics, management approach, or management history (Bettinger, 2011). The accurate knowledge with regard to stand-level forest characteristics over large-scale landscapes also will be beneficial to make a strategic planning in both commercial uses and conservation issues. As one of the stand-level forest variables, age structure can be efficiently employed to assess the stages of stand development and the degree of tree maturity (Cohen et al., 1995). Particularly, knowing locations or amounts about pre-merchantable tree areas will be valuable in that it provides information about the future bioenergy potential and timber market investment.

In chapter 3, we examine FIA data and FIA program tools for the estimation of the amount of pre-merchantable trees in Georgia at the county-level. In addition, we classified premature forest stands of which age is 15 or under 15 years using Landsat TM imagery in southeastern Georgia. We adapted multiple technologies, including Maximum Likelihood Classification (MLC), regression analysis, and *k*-Nearest Neighbor (*k*NN), and compared the pros and cons of each technique in terms of the accuracy and data application. In doing so, we tried to identify which classifiers will be more suitable for the purpose of estimating forest age structure. We added research about the estimation of forest stand-level characteristics using Landsat imagery in the southern U.S., where such research was not thoroughly investigated. Typically, we employed overall accuracy and the kappa coefficient as standard methods to find which techniques were more suitable for estimating forest stand age structure. In addition, in the use of each technique we consider which further steps are required to enhance the accuracy, and we consider limitations in the use of Landsat imagery for that purpose. Therefore, the usefulness of Landsat imagery in combination with various image processing classifiers were assessed for the purpose of identifying premature stands based on the results of the classification processes.

Given the estimates of forest stand-level structures using satellite imagery, field inventories, and various sale characteristics, we can consider various models which are related to forest stand development and/or the change of timber market prices. The accuracy for the estimates of forest stand-level variables and related sale characteristics will be essential factors for making a better model. In chapter 4, we use Timber Mart South (TMS) data from 1998 to 2007 and employ the hedonic pricing method on stumpage price changes based on TMS data from 11 southern U.S. states. We analyze how the stumpage price of pine sawtimber is influenced by various timber sale characteristics. Therefore, we make a multiple regression model of stumpage price to estimate the implicit values of sale characteristics from commodity value. Although the hedonic pricing method is applied to the timber market many times, there is limited published research conducted in the southern U.S. Further, sale characteristics are relatively limited items, which make it difficult to investigate how a variety of sale characteristics impact the change of stumpage price. We typically adapted the quadratic transformation to estimate parameters of threshold models, providing the estimation of inflection points, which are maximized or minimized points. Given the requirements for up-to-date stumpage market information, a model to estimate timber price in relation to timber sale characteristics will be useful to both timber buyers and sellers in that it provides the implicit values of sale characteristics for stumpage price changes in southern United States, and thus we can expect to have better insight into the trends of stumpage price changes and anticipated demand for each sale input.

In sum, in chapter 2 we present a review of peer-reviewed research regarding the estimation of forest parameters using Landsat imagery. In chapter 3 we compare tools for the FIA program to estimate the quantitative information of pre-merchantable stand areas, and we classify premature forest areas using Landsat imagery with various techniques in southeastern Georgia and compare the merits and demerits in each method in terms of overall accuracy and the kappa coefficients. In chapter 4, we make a hedonic model for the change of stumpage price to estimate the implicit values of sale characteristics for stumpage price in southeastern United States, and finally, in chapter 5 we present our conclusions.

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CHAPTER 2

REFLECTIONS ON THE ESTIMATION OF STAND-LEVEL FOREST CHARACTERISTICS USING LANDSAT SATELLITE IMAGERY

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Abstract

Considerable attention has been applied to the use of Landsat satellite imagery in estimating forest conditions. Here, we focus on the stand-level forest characteristics that have been estimated with this imagery, the classification techniques that have been employed, and the ancillary data that have been used to assist in the process. Based on the peer-reviewed research we located, some gaps in the literature concerning image classification techniques remain. With regard to the algorithms employed in the image classification processes, various forms of regression analysis seem to be the most often used techniques, while the *k*-Nearest Neighbor (*k*NN) technique has been increasing in value, yet other classification techniques (e.g., kriging, neural networks) have only begun to be explored and may have value in some situations. In terms of specific forest conditions, the use of Landsat satellite imagery for estimating above ground biomass has been heavily investigated, and opportunities continue to exist for refining classification techniques aimed at the classification of forests by discrete age classes, by contiguous species groups, and by height classes.

1. Introduction

Satellite imagery can be used to meet, at various scales, the information requirements of forest managers (Sayn-Wittgenstein, 1986). In fact, broad-scale forest landscape information and associated land cover maps are often developed using data (reflected or emitted electromagnetic energy) acquired by a remote sensing device contained in satellites (i.e., satellite imagery) or other aerial platforms (e.g., air planes). Satellite imagery has been especially valuable as a source of information for estimating forest conditions across broad landscapes (Maselli et al., 2011). The spectral reflectance values contained in the smallest component of a digital image (the pixel), along with other synthetic combinations of these, can be of value in estimating stand-level forest characteristics. These stand-level estimates of forests can then facilitate strategic planning of forested areas where field-based forest inventories are too expensive to obtain (Holmgren et al., 2000).

For nearly 40 years, ecologists and forest managers have utilized Landsat satellite imagery for Earth observation, natural resource management, and research purposes, and thus this imagery has become widely-accepted as a source of landscape information (Mäkelä and Pekkarinen, 2004; McRoberts, 2011; Loveland and Dwyer, 2012). However, recent technological issues cloud the future of the Landsat program (Chen et al., 2011) and currently the imagery captured by Landsat 7 sensors contains linear data gaps that stretch across each scene, resulting in about 22% data loss (Loveland and Dwyer, 2012). This problem is caused by the failure of a component called the scan line corrector (SLC) in the satellite (Chen et al., 2011). Methods for addressing data gaps in this imagery can include histogram matching (Rulloni et al., 2012) or other advanced techniques (Zhu et al., 2012). In lieu of Landsat 7 satellite imagery, similar (from a spectral and spatial resolution point of view) Landsat 5 imagery was available until recently, since the SLC had not failed in this system. However, in November 2011 the U.S. Geological Survey terminated Landsat 5 imagery collection to investigate a potential failure the data retrieval system, and at the time of this review, imagery collection had been paused (U.S. Geological Survey, 2012). Although the timeline for operability is unclear, a new Landsat satellite (the Landsat Data Continuity Mission, or LCDM) is expected to be placed into service in 2013 (Irons et al., 2012). Regardless of these operational issues, the advantages of using data acquired through the Landsat satellite imagery program include the cost (now freely available) and the spatial resolution (30 m *x* 30 m) of the raster data. Further, a wealth of literature is available to assist with data processing issues (a recent keyword search in ScienceDirect using "Landsat" yielded over 16,500 papers). And, whether current or historical data are of interest, with both Landsat (7 and 5) satellite systems, a few pre-processing issues have been addressed prior to acquisition by a user of the information: each scene is radiometrically processed and calibrated (Markham and Helder, 2012; Irons et al., 2012), and raw data have been converted from radiance (in raw digital numbers (DN)) to reflectance values (measured at the sensor) for each band of energy (Chander et al., 2009).

Landsat satellite imagery has been frequently used to describe broad-scale landscape processes occurring on Earth, such as land use or land cover change (e.g., Huang et al., 2009; Lasanta and Vicente-Serrano, 2012) and fire extent and severity (e.g., Wimberly and Reilly, 2007; De Santis et al., 2010). Of interest to our analysis is the ability of Landsat satellite imagery to help describe finer-scale structural conditions of forests, or summaries of tree conditions at a level of what many forest managers consider the *stand* (1-20 ha) (Mäkelä and Pekkarinen, 2004). A forested stand is a uniform collection of trees found in a contiguous area, managed separately, and distinguishable from other nearby collections of trees (Nieuwenhuis, 2010). Stands can defined by vegetative characteristics (e.g., tree age, tree species), physical features (e.g., roads and streams forming a natural edge), management approach (even-aged forest, uneven-aged forest), or management history (e.g., previously thinned, previously fertilized) (Bettinger, 2011). Stand-level forest characteristics are sets of essential information for strategic forest planning purposes, for forest sustainability analyses, and for stand-level silvicultural prescription development. These include the amount of above ground biomass (AGB), the total timber volume, the average tree diameter at breast height (DBH), the average tree height, the average age, the crown closure, and the density (basal area or trees per unit area).

With estimates of forest characteristics, one may be able to develop informed forest management schemes (Newton et al., 2011), to accommodate large-scale landscape planning processes (e.g., Bettinger et al., 2005), or to simply satisfy a forest landowner's informational interests. However, while estimating stand-level forest characteristics may be the objective of many endeavors, understanding the accuracy of the estimates and the associated uncertainty is equally important (Miegs et al., 2011; Shupe and Marsh, 2004). Depending on the situation, error associated with stand-level forest characteristics may be too high for some planning purposes (Mäkelä and Pekkarinen, 2004). Further, the diversity encountered in site quality and forest management practices employed across a landscape can introduce unexpected variation into remotely sensed data (Kimes et al., 1996), and in some cases the error observed may be difficult to overcome at the pixel level (Powell et al., 2010).

In this review paper, we analyze and summarize recently published research related to the estimation of stand-level forest characteristics with Landsat satellite imagery. In the course of this discussion we outline the advantages and disadvantages of using Landsat satellite imagery and identify gaps in knowledge. The broad objectives for this review include describing challenges that have been encountered in using Landsat satellite imagery for estimating stand-level forest characteristics, describing the techniques that have been employed to estimate stand-level forest characteristics with Landsat satellite imagery, and outlining the usefulness and suitability of using auxiliary data to help describe stand-level forest characteristics. In the course of this review, we describe trends that are evident in association with these processes, and we identify some gaps in knowledge that could be addressed with further research.

2. Methods

We reviewed published peer-reviewed literature that described processes for estimating stand-level forest characteristics using Landsat satellite imagery. We acknowledge that some published work focused on this subject can likely be located in non-peer reviewed sources. In order to remain consistent in our approach, and to avoid cases where similar work has been published in both peer-reviewed and non peer-reviewed outlets (e.g., a proceedings paper and a journal article both describing same work), we strictly concentrated on peer-reviewed literature from international English language journals. If the decision were to have been made to review non-peer reviewed work, this would likely require a more extensive search of the gray literature. Unfortunately, some advances may have been omitted by concentrating on peer-reviewed research (e.g., Lee and Nakane, 1997). The time frame of the published literature was 1995 and

2012 in order to focus on relatively new trends in research. The geographical scope of the analyses described in the literature included any effort, world-wide, that described the development of stand-level forest characteristics using Landsat TM or ETM+ satellite imagery. In order to locate peer-reviewed published literature, multiple Internet-based search engines were employed: Science Direct, Informaworld, SpringerLink, and Google Scholar. The search for literature relied primarily on keyword queries (e.g., "Landsat", "forest", "structural parameters"). Upon locating published literature, the reference section of each was explored for other sources of recently published information. We were interested only in locating published literature that described the estimation of certain stand-level forest characteristics: AGB, timber volume, average tree height, average age, crown closure, and density (basal area). An omission of published literature is possible, and the authors take full responsibility for such problems. Literature describing techniques for estimating or detecting forest disturbances were not included in this review, nor were literature describing how one might classify land use or land cover change. For each piece of literature that met our specifications, we recorded the journal, the stand-level forest characteristics that were estimated using Landsat satellite imagery, the study area where the research was conducted, and the analytical technique that was employed. Discussion and conclusions sections, particularly, were advised to locate areas for improvement in forest character estimation procedures.

3. Results

To suggest that there is a large volume of peer-reviewed literature involving Landsat satellite imagery would be an understatement. As we noted, a recent query of the ScienceDirect database using the single keyword "Landsat" yielded over 16,500 articles. Through refinements of the search process and after examination of numerous peer-reviewed articles, we narrowed the scope of our analysis to a little over one hundred papers that were published in thirty-eight different journals. Among the journals, we observed the highest rate of publication of research on this subject in the following three: *Forest Ecology and Management*, *International Journal of Remote Sensing*, and *Remote Sensing of Environment*. As we found in our search of the literature, there has been general increase in publication of peer-reviewed research involving stand-level forest characteristics using Landsat satellite imagery over the period 1995 to 2006. Since then, however, there has been a slight decrease in the number of peer-reviewed papers published on this subject.

3.1 Stand-level forest characteristics typically estimated using Landsat satellite imagery

Doubt concerning the ability of Landsat TM and ETM+ satellite imagery to sufficiently describe forests and adequately inventory forest conditions was expressed nearly 25 years ago (Ahern and Horler, 1986). Concern lies partly in the fact that the spectral resolution of Landsat TM and ETM+ imagery is confined to seven specific frequencies within the electromagnetic energy spectrum, although using these, and synthetic combinations of these (e.g., NDVI), a differentiation can be made of main tree species groupings and of the general forest health condition. Concern also lies partly in the spatial resolution of the data (30 m *x* 30 m grid cells). However, given the wide coverage of a single Landsat scene (185 km *x* 171 km), interest has been strong in the ability of the imagery to further facilitate the development of high-quality, broad-scale forest characteristics. Some stand-level forest characteristics, such as timber volume and average tree age, are important for planning and management purposes, while others (AGB) are perhaps more important for sustainability and carbon sequestration, carbon accounting, and carbon dynamics purposes. Over the last fifteen years, timber volume, stand age, forest density, tree crown closure, and average tree height have all been estimated to some reasonable degree of accuracy for various parts of the world using Landsat satellite imagery. For example, Jakubauskas (1996) found moderate to high correlations between basal area (a measure of density), average age, and dominant height of lodgepole pine (*Pinus contorta var latifolia*) trees in Yellowstone National Park (USA) and spectral responses contained in the various bands of Landsat satellite imagery. Trotter et al. (1997) described several techniques for reasonably estimating timber volume when using Landsat satellite imagery, and discussed the relative accuracy of doing so at the pixel-level and larger scales. Reese et al. (2002) also developed estimates of timber volume, and while the accuracy of their estimates was relatively low at the pixel level, over larger scale areas (aggregates of 100 ha) the error was reduced to about 10% RMSE. Further, work performed by Kimes et al. (1996) indicated that the ability to estimate average stand age of temperate coniferous forests with root mean squared error of 5 years is possible, and Wulder et al. (2004) suggested a process for arriving at stand ages that had an associated 2.4 year standard error. However, in tropical forests, stands that are 15 years of age or greater may appear spectrally similar to nearby mature forests, suggesting that stand age determination may be more challenging (Steininger, 2000). Others (Wulder et al., 2004; Sivanpillai et al., 2006) have suggested that normalized difference vegetation index (NDVI) or a wetness index were also necessary to more accurately estimate stand ages in certain forests. Crown closure of trees is perhaps even more difficult to estimate, given that reflectance values are for the upper crown area of a forest, and may likely not account for understory trees. In one analysis of a temperate coniferous forest, when broad crown cover classes were assumed, crown closure was underestimated, and when fine (10% intervals) classes were assumed, crown closure was overestimated (Gill et al., 2000). Causes of concern relate both to the model used to estimate crown cover from Landsat satellite imagery, and the techniques employed to estimate crown cover from field validation (inventory) plots.

Estimating stand-level forest characteristics can be challenging with remotely sensed imagery because as some have found, each type of vegetation can emit or reflect different levels of electromagnetic energy. Average stand heights, for example, are difficult to estimate with satellite imagery alone, and accuracy may vary by forest type for these reasons (De La Cueva, 2008). Stand-level forest density estimates may be closely related to infrared reflectance values of certain forest types, but accuracy can vary between forests of the same density yet possessing a different management history (e.g., planted vs. naturally regenerated), and accuracy can vary between forests of the same density yet containing a different dominant tree species (Sivanpillai et al., 2006; Meng et al., 2009). Stand density is closely related to AGB, and a large set of published research from around the world has focused on AGB estimation. Some examples of these include work performed for forests in India (Roy and Ravan, 1996), Sweden (Fazakas et al., 1999), Brazil, Malaysia, and Thailand (Foody et al., 2003), the United States (Zheng et al., 2004), China (Zheng et al., 2007), and Canada (Wulder et al., 2008). Some have observed a non-linear relationship between stand attributes such as AGB and reflectance values from satellite imagery, perhaps due to the typical successional growth trend for most tree species (Hall et al., 2006). In the last few years research regarding forests in Asia, Europe, and North America has dominated the literature according to our search criteria. Most of the published work has been performed for North and South American landscapes, northern Europe, and various parts of Asia. A limited amount of research from our search has been performed for forests of Africa and Oceania. However, recent activity in AGB estimation of African forests has been reported (Avitabile et al., 2012).

3.2 Modeling techniques employed for stand-level forest character estimation

A number of modeling techniques or analytical tools that can be used in conjunction with Landsat satellite imagery to estimate stand-level forest characteristics, and in some cases it may be difficult to conclude that one technique is superior to others (e.g., Powell et al., 2010). To be of value in estimating stand-level forest characteristics, a modeling technique must be able to differentiate forest conditions into categories (strata, classes) or be able to assign a continuous value (e.g. timber volume) to each pixel in a manner that these can sufficiently facilitate planning or analysis purposes. Correlation analysis and various forms of regression have been widely used in conjunction with Landsat satellite imagery for estimating forest characteristics. It seems that regression analyses will generally require as independent variables some transformation (e.g., logarithmic) of the original Landsat spectral data or synthetic data (i.e., a composite, or a specific combination of data) derived from various Landsat spectral bands. For example, Zheng et al. (2007) developed regression models to estimate forest biomass in south-central China and noted that leaf area index and NDVI were necessary independent variables for the prediction of forest biomass. Each of these, of course, was developed from the original set of Landsat spectral reflectance values: red and near infrared (NDVI), and red, near infrared, and shortwave infrared (LAI). Stand age and forest type were also necessary independent variables, and in this case, stand age was deduced in a round-about manner using biomass as a variable (before development of the biomass regression model). Roy and Ravan (1996) developed empirical models with multiple linear regression for estimating forest biomass levels. In this early work, they observed that brightness and wetness indices (developed from a tasseled cap transformations of several of the spectral reflectance values) were strongly positively correlated with forest biomass levels, and thus the regression model developed included this type of synthetic data. Mallinis et al. (2004) used original Landsat satellite imagery reflectance values along with similar transformations of synthetic data to estimate density, basal area, basal volume, and biomass of forests in northern Greece. In assessing their multiple linear regression models, Mallinis et al. (2004) suggested that forest density and basal area could be better predicted than forest biomass or timber volume, and that a vegetation index (a combination of red and near infrared reflectances) was necessary to improve the quality of the models developed. These types of results are not broadly applicable, however as others (e.g., Lu et al., 2004) have pointed out issues of consistency (e.g., shortwave radiation important) and inconsistency (e.g., vegetation indices developed from red or near infrared radiation not as important). As these and other research results have shown, it may be difficult to select suitable satellite imagery data for a specific regression analysis due to variations in forest stand conditions and the complex relationships between spectral reflectance values (or the synthetic indices developed from these) and select forest characteristics (Lu et al., 2004).

The *k*-Nearest Neighbor (*k*NN) technique of image classification (Moeur and Stage, 1995) and assignment of stand-level forest characteristics to raster database pixels has been used extensively in Scandinavia for at least 15 years (Gjertsen, 2007), and in North America for nearly a decade (McRoberts, 2012). When employing the *k*NN technique, stand-level forest characteristics for each pixel are predicted as weighted averages of the nearest *k* reference plots (field inventory plots) whose location within the satellite imagery is represented by similar spectral reflectance values (Fazakas et al., 1999). The forest characteristics estimated are in some cases linear combinations of observations, and in other cases inverse-squared and (or) distance weighted. The *k*NN technique assumes that pixel values of stand-level forest characteristics depend only on forest condition, as represented by spectral values of the various bands of electromagnetic energy captured by the remote sensor (Fazakas et al., 1999). The classification process is based on the similarity in a covariate space between these, and the technique can be considered non-parametric and either univariate or multivariate (McRoberts et al., 2007). It is suggested that the main reasons a *k*NN technique is used are the simplicity and flexibility of the process, the ability to produce statistical estimates, the ability to use the process with categorical data, and the ability to create landscape maps of forest characteristics (Gjertsen, 2007; McRoberts, 2012). Although *k*NN techniques are relatively practical to implement and are regarded as suitable techniques for the estimation of stand-level forest characteristics (McRoberts et al., 2007; McRoberts, 2009), one problem with the use of *k*NN techniques is that some of the errors associated with the classification process might be considered systematic and the associated estimates might be considered biased. These errors may be caused by factors that affect the measurements in a certain direction across the sample, in turn influencing the averages of forest characteristics across the landscape (Gjertsen, 2007). Other factors causing error include (a) forest conditions that are not represented well by the field-based inventory data, and (b) weak association between spectral values and forest conditions, particularly in mixed forests (Gjertsen, 2007). The computational intensity of applying a *k*NN technique to an entire Landsat satellite image has also been noted as a concern (Finley and McRoberts, 2008; McRoberts et al., 2007), yet with advances in computer technology, this will likely be alleviated to some extent. However, in order to save computation costs, Meng et al. (2007) suggest that remote sensing data reduction techniques (layer combination, principle components analysis, etc.) can be used.

In conjunction with Landsat satellite imagery, a *k*NN technique was used to estimate stand-level timber volume and basal area of forest compartments within a Swedish National Forest (Holmgren et al., 2000). Here, high timber volumes per unit area were underestimated and low timber volumes per unit area were overestimated (the estimates smoothed out the data), and it was noted that the bias could be reduced when ancillary data (site index, age, average height) were also included in the estimation of timber volume. Low and high volume estimates were found to be less accurate in other studies as well (e.g., Reese et al., 2002). Mäkelä and Pekkarinen (2004) employed the *k*NN technique in order to estimate stand-level timber volumes by tree species, and while high levels of accuracy were not achieved, approximate volume estimates were derived where no other forest information was available. In addressing the selection of *k*, trials can be conducted, along with assessments of error and bias, and conclusions can be drawn as to the *k* that optimizes a certain decision criterion, such as the root mean squared error (McRoberts, 2012). Trotter et al. (1997) suggested that the *k* (number of neighbors) needed to be large (≥ 15) in order to obtain reasonable accuracy at the pixel-scale, yet this biased the outcomes (timber volume) at larger scales. Mäkelä and Pekkarinen (2004) observed that once *k* exceeded ten, the error of timber volume estimates decreased only slightly, thus $k = 10$ was suggested. Kajisa et al. (2008) showed that error in timber volume estimations using a *k*NN approach decreased as *k* increased up to five, after which the error again increased. Meng et al.

(2007) suggest that a non-parametric Kolmogorov-Smirnov (KS) test can be employed to determine whether the estimates based on a specific *k* are significantly different from others.

A slightly different type of nearest neighbor technique based on canonical correspondence analysis, the Gradient Nearest Neighbor (GNN), has also been used in conjunction with Landsat satellite imagery to estimate stand-level forest stand characteristics. The GNN technique developed by Ohmann and Gregory (2002) utilized relationships between vegetation and environmental information that included climatic (precipitation, temperature), topographic (elevation, slope, aspect), and geologic data. Stepwise canonical correspondence analysis based on the first eight canonical correspondence analysis axes (weighted by their eigenvalues) was used to identify a single field-measured inventory plot that was nearest to each pixel in the eight-dimensional gradient space. Based on predicted basal area, Landsat spectral reflectance information explained most of the variance in the canonical correspondence analysis (yet only 15%), followed by climate, location, and topography. Ohmann and Gregory (2002) observed that this technique was comparable to others that had been applied in the area of interest (Pacific Northwest, USA), and like other techniques, it predicted poorly at small scales, and very well at larger scales. Similar techniques were employed by Powell et al. (2010) to estimate AGB using Landsat satellite imagery, and Pierce et al. (2009) to estimate forest fuel levels.

Various other analytical techniques have been used in an attempt to estimate stand-level forest characteristics from the information provided by Landsat satellite imagery. Conversion tables, for example, that relate a classification (unsupervised, supervised, etc.) of satellite imagery to stand-level forest characteristics, can be employed. Luther et al. (2006) and Labrecque et al.

(2006) describe a technique for estimating forest biomass from Landsat satellite imagery. Here, an unsupervised classification of NDVI was performed and a large set of spectral clusters were developed. Then, using a set of training data developed for each tree species group and forest structural class, the dominant tree species group and a forest structure class were assigned to each pixel based on the spectral cluster, and forest biomass was then assigned to each pixel based on conversion table relationships. Similar to Holmgren et al. (2000), biomass was overestimated in younger and more open forest areas, and underestimated in older and more dense forest areas.

A neural network is a classification technique that has the ability to address non-linear problems by learning patterns and relationships, and by generalizing results in light of inherent variation in the data (Kimes et al., 1996). A neural network usually contains a large number of processing units that are linked by weighted connections, and the weights are adjusted (updated) through numerous iterations through the network as the relationships between the remotely sensed data and the desired outputs arise (Foody et al., 2001). Spectral reflectance values may have a complex or non-linear association with forest characteristics (Ingram et al., 2005), thus a neural network may be trained to use various satellite image spectral bands (and their synthetic derivatives) and to weight their values (yet not necessarily remove them entirely from the analysis) as appropriate to derive predictive relationships (Boyd et al., 2002). As with GNN techniques, these processes can utilize climatic, topographic, and geologic data to help inform the relationships, and as with a supervised classification processes, a set of training data is necessary to learn about these relationships. As an example of the use of this type of process, Foody et al. (2001, 2003) employed neural networks for AGB estimation using several vegetation indices derived from Landsat spectral bands.

In addition to regression and neural network techniques, Liu et al. (2008) examined the use of decision trees to estimate forest ages from Landsat satellite imagery. Decision tree approaches select a variable of interest, split the range of valid values of the variable into two groups, and assess the quality of both approaches (child nodes) in describing a desired outcome. Further exploration along each limb of the tree is then possible. The process continues along this type of divide-and-conquer behavior until terminating rules suggest that a suitable model was been created. Liu et al. (2008), in estimating forest successional stages, found that decision trees were as useful as neural networks in this regard, while also being somewhat easier to understand from a conceptual point of view. Alternatively, Foody et al. (1996) used both a maximum likelihood classification and an object-based process to assign Landsat satellite image pixels to the forest age class within which it had the highest probability of membership based on spectral reflectance properties. The maximum likelihood classification process relied solely on spectral information, while the object-based process relied on both spectral and spatial information, since groups of adjacent pixels were classified together. In the ensuing analysis, Foody et al. (1996) suggested that the object-based process, because it employed both spatial and spectral information, was slightly better for estimating forest age classes in tropical forests.

Meng et al. (2009) describe ordinary kriging (linear), universal kriging (polynomial), cokriging (incorporating inter-variable correlation), and regression kriging (using simple or multiple linear regression) as techniques for using Landsat satellite imagery to estimate basal area levels for southern United States pine forests. Kriging is the process of interpolating a certain value (perhaps timber volume) of an unknown area based on nearby observations. In Meng et al. (2009), regression kriging seemed to display the most promise for spatial interpolation among known data points. Viana et al. (2012) also describe an application of ordinary, universal, and regression kriging to the estimation of forest biomass in Portugal, and although these were not generally superior to an ordinary least squares regression approach, the regression kriging technique was able to generate a spatial map of uncertainty for estimates of biomass. As both studies point out, and as with neural networks, more attention needs to be applied to these techniques to understand how they can improve upon to regression and nearest neighbor imputation techniques for estimating stand-level forest characteristics.

3.3 Combined use of Landsat with ancillary data

The suggestion that satellite imagery needs to be integrated with ancillary information in order to successfully describe forest conditions is an old one (e.g., Sayn-Wittgenstein, 1986). As has been mentioned in the description of some of the classification techniques noted above, Landsat satellite imagery has often been used for stand-level forest characterization in combination with other ancillary data, and in some of these cases, the accuracy of the estimated stand-level forest characteristic has subsequently increased. Ancillary data can include field-based forest inventory data (plots, points, transects, or other empirical data), or topographic (e.g., slope, aspect, elevation), geologic, soils, land ownership, and climatic (e.g., air temperature, precipitation) information. Some of these data are represented by continuous surfaces, while others are represented by points or small areas. Some of these data are presented as continuous values (e.g., timber volume, biomass, tree density), while others are categorical (land owner class, soil type, age class). The estimation of AGB seems to benefit greatly with the introduction of field-based measurements even though at times the process can be challenging (Hall et al., 2006), and the estimation of timber volume seems to benefit from prior knowledge of average stand heights (Magnusson and Fransson, 2005), since tree height is a key component in many equations for estimating timber volume. Avitabile et al. (2012) also show that the inclusion of land cover maps as ancillary data may be necessary in some areas of the world when estimating biomass levels. In mountainous areas, topographic (aspect, slope) information may be necessary in order to better differentiate characteristics such as average stand age (Kimes et al., 1996). For areas where field-based forest inventories are available, Wulder et al. (2008) describe a polygon decomposition approach that harmonizes forest inventory estimates of biomass with pixel-based estimates from remotely sensed imagery by summing the pixel-based biomass estimates for each pre-defined forest stand polygon. However, when using ancillary data such as field-measured inventory plot summaries (or tree lists) in conjunction with an image classification process (e.g., *k*NN, GNN), error (whether systematic or random) in the field measurements can contribute to the total error observed in the resulting landscape classification (Ohmann et al., 2012).

Many of the nearest neighbor classification techniques utilize national forest inventory data, or field plots collected at specific locations systematically distributed across a given country. This is the case perhaps because national forest inventory data is often more freely available (in contrast with data collected by private organizations) to researchers through limited arrangements (Smith, 2002; Reese et al. 2003), perhaps because of the wide coverage of national inventories, and perhaps because of the rich information these generally contain. Examples of these efforts include Holmgren et al. (2000), Tomppo et al. (2002), McRoberts et al. (2007), Ohmann et al. (2012). Some knowledge of the design and analysis procedures of these broad-scale, multi-resource inventory systems is necessary to utilize the available data. Field data can be used to help in the classification process, and the resulting estimates from a classification process can also resemble closely the field data. For example, field data can be used to help estimate forest heights for each grid cell that is not represented by field data.

LiDAR (Light Detection and Ranging) data, which is also remotely sensed, utilizes the same range of electromagnetic energy (ultraviolet to near infrared) as does Landsat satellite imagery. LiDAR has been assessed for use in stand-level forest characterization in conjunction with Landsat satellite imagery. The relationship is complementary because LiDAR data can provide fairly accurate estimates of forest characteristics in the vertical plane, while Landsat can provide extensive coverage of a landscape in the horizontal plane. Lefsky et al. (1999) combined Landsat estimates of stand age and LiDAR estimates of AGB to model forest productivity, and subsequently estimated aboveground net primary production of wood based on stand age and biomass. Hudak et al. (2002) combined LiDAR and Landsat satellite imagery, then applied four types of classification processes in an effort to develop a database of forest heights. In many cases, LiDAR data is not as spatially extensive as Landsat satellite imagery, yet stand-level forest heights can be fairly accurately estimated with LiDAR data, therefore combining Landsat satellite imagery with estimated forest heights can help improve stand height estimates for areas not covered by LiDAR data. In essence, LiDAR-derived samples of forest heights could be used as training sites for a broader-scale forest classification process.

4. Discussion

Earlier we noted a general increase in the number of peer-reviewed published papers regarding stand-level forest characterization over the analysis period (1995 to 2006) that were based on the use of Landsat satellite imagery. The variety of techniques and applications suggested that international interest in developing and reporting techniques for stand-level forest character estimation has been increasing. Interestingly, we found most of the related papers in three well respected, peer-reviewed journals that were international in scope (*International Journal of Remote Sensing*, *Remote Sensing of Environment*, and *Forest Ecology and Management*). However, the literature we reviewed was also located in 35 other journals, and other literature may have been published in non-English language journals. Further, we primarily used keyword queries for locating peer-reviewed papers, and we only concentrated on reviewing work published in peer-reviewed scientific journals. Therefore, it is possible that some seminal work was omitted from our review. In sum, we consider our work to represent a sample of the knowledge regarding stand-level forest character estimation using Landsat satellite imagery rather than a thorough and complete assessment of such.

Through research that has been conducted on multiple stand-level forest characteristics within the same or similar geographic area (e.g., Cohen et al., 1995; Jakubauskas, 1996; Fazakas et al., 1999; Steininger, 2000; Holmgren et al., 2000; Ohmann and Gregory, 2002; Reese et al., 2002; Franklin et al., 2003; Reese et al., 2003; Lu et al., 2004; Mallinis et al., 2004; Freitas et al., 2005), one *could attempt to* rank the suitability of the modeling techniques by various measures of accuracy. However, one cannot conclude which stand-level forest characteristic(s) will be more suitably estimated, because accuracy will differ according to research area and technique employed, and thus results will likely vary. Likewise, ranking stand-level forest characteristics by the ability to accurately describe their level across the landscape would not be consistent because these too differ by study area, classification technique utilized, and ancillary data employed. While a number of studies have been employed to determine forest characteristics from Landsat imagery, there are few directly comparable studies to allow one to adequately ascertain why some relationships are more easily ascertained than others, within an ecoregion or across ecoregions. Within this body of research one finds distinct differences in forest types studied, image classification methods employed, and management objectives considered that make these types of issues difficult to address. In addition to the influence of study objectives on the issue of transferability of methods across ecoregions, it remains to be seen whether the successes claimed through analyses of the accuracy of predictions will generally be transferable to other geographic areas given varying physiographic and vegetative conditions.

From a pure accounting point of view, of the stand-level forest characteristics estimated using Landsat satellite imagery, average tree height, crown closure, and average stand age have been addressed relatively less so than others. Landsat satellite imagery can provide a horizontal perspective of the landscape, therefore unless correlations are made between spectral responses and dominant tree species and forest age (which an association can then be made to average height), ancillary data describing vertical relationships (such as LiDAR data) may be necessary. Even though there is relatively little research on the estimation of tree heights, the results are noteworthy. In one case, when only two classes of heights were estimated from Landsat satellite imagery, the accuracy was fairly good (Franklin et al., 2003). Lu et al. (2004) also found the correlation between average stand height and vegetation indices derived from Landsat imagery to be relatively high. However, the combined use of ancillary data and satellite imagery may facilitate a synergistic effect that can overcome some of the disadvantages of using only satellite imagery. Further, ancillary information, such as broad land cover classes, inventory plots, or LiDAR data may be of value in increasing the accuracy of stand-level forest characterization, particularly in areas that contain a mixture of coniferous and deciduous tree species (McRoberts, 2009). LiDAR data seems especially useful for estimating forest structures and stand height. However, LiDAR data are limited in terms of coverage over large areas.

Each image classification technique has its limitations, and selection of one is dependent on the application and the environment (Boyd et al., 2002). Regression analysis that uses remotely sensed imagery and explicit forest measurements has been the most commonly used methodology for estimating stand-level forest characteristics with Landsat satellite imagery, yet nearest neighbor imputation techniques are gaining in popularity. Regression analysis has an advantage: one generally needs less data than is required for *k*NN techniques, as *k*NN techniques can use both continuous data (typically used in regression) geographical (Bååth et al., 2002) or categorical data. Based upon a limited number of reference data, one can develop a regression model and use the fitted equation to estimate stand-level forest characteristics for other areas. However, when the regression equation(s) contains a high level of variation or when the reference data are concentrated within a limited area, estimates of stand-level forest characteristics using a regression model could contain more uncertainty. In addition, one will likely encounter the problem of extrapolating predictions of stand-level conditions beyond the range of data that was used to develop the regression model, and this could result in absurd predictions, such as negative timber volumes.

According to various authors of the literature we reviewed, *k*NN techniques are considered easy to implement and can be used to develop a reasonable forest inventory. One crucial issue in the use of *k*NN techniques is the assumed number of *k*. There are several ways in which one can obtain the optimal or appropriate *k* value, such as employing the Kolmogorov-Smirnov (KS) tests and examining cumulative distribution functions (CDF) or preliminary trials, or applying cross-validation or bootstrapping processes to assess modeling behavior. Unfortunately, the accuracy of a *k*NN technique is strongly influenced by the selection of value *k*, thus careful consideration of *k* should be based on knowledge generated from tests such as these. Further, single-neighbor (k = 1) imputation processes generally result in lower local-scale accuracy than what can be obtained with other techniques, as estimates are subject to variability within a spectral space (Pierce et al. 2009). Another disadvantage of using *k*NN is that one needs sufficient reference data, distributed across the study area, to adequately estimate stand-level forest characteristics, therefore it is challenging to use this approach over large areas without a reasonable set of reference data. Thus a wider range of variability across a landscape should be sampled for the imputation process to work effectively (Pierce et al., 2009). However, it may be erroneous to assume that imputed pixel values can be independent of the geographic location of reference data, therefore a sub-set of a Landsat satellite image or geographical constraints on the neighborhood have been suggested (Fazakas et al., 1999).

Even though the accuracy of estimating stand-level forest characteristics by neural networks and certain kriging techniques has been shown to be relatively high, these have not been widely tested. Further, regression-kriging is thought to be more sophisticated and computationally demanding than other techniques (Viana et al., 2012). Therefore, we suggest that this is one area for further research to pursue. It is difficult to compare techniques when they have been employed on different landscapes for different purposes. While some research has employed several techniques in order to directly compare their efficiency and accuracy, through this review we failed to arrive at a consistent ranking in techniques due to non-standard test instances, differences in test databases, and differences in approaches employed. However, one can conclude that, based on the accuracy of certain stand-level forest character estimates, regression analysis, *k*NN and neural networks are all relatively good image classification techniques in certain situations.

As one of the most important medium-resolution remotely sensed programs, the use of Landsat satellite imagery for estimating stand-level forest characteristics has proven practical, given tests of overall accuracy (Cohen et al., 1995; Roy and Ravan, 1996; Foody et al., 1996; Steininger, 2000). Accuracy tests have involved correlation analysis, and determinations of RMSE and bias. Even if results of research have shown high levels of accuracy in estimating stand-level forest characteristics, transferring these models to other geographical areas has not been assessed. We can also infer that the amount and extent of reference data employed can influence the overall accuracy of the classification process. Some issues concerning the use of satellite imagery for estimating stand-level forest characteristics remain. The spectral reflectance values of pixels near the edges of forests, for example, can be affected by neighboring land use conditions, thus the correlation between spectral reflectance values and stand-level forest characteristics can increase if edge pixels are excluded from an analysis, however this may impart bias into the estimated stand-level forest values (Mäkelä and Pekkarinen, 2004). Steininger (2000) also suggested that precipitation levels may cause between-year differences in leaf area of forests, and these could affect near- and middle-infrared canopy reflectance values of forests with similar ages and similar levels of biomass. Thus the issues concerning the temporal vintage of Landsat satellite imagery (e.g., collected during a drought or after a tropical cyclone) may need to be considered along with changes in the phenology of plants (Lehmann et al., 2012). Further, at the pixel scale, the relationship between estimates of forest characteristics can be significant, but usually are weak, yet when aggregated to a scale representative of a typical forest stand, the accuracy of classification approaches can be acceptable (e.g., Trotter et al., 1997; Reese et al., 2002; Gjertsen, 2007).

Satellite remote sensing technology is of great benefit to humankind, yet the systems are not perfect. For example, satellite images are acquired over different Earth surface albedo (water, forest, soil, etc.), and satellite sensors need to accommodate the potential observed variation in the range of brightness values. How the sensors handle changes in brightness values is therefore important. A radiometric sensor is considered saturated when the input signal exceeds the maximum measurable signal of the sensor. In the newer ETM+ imagery, when saturation is approached due to changes in brightness values, greater radiometric sensitivity is applied by the sensor until saturation is reached (Karnieli et al., 2004). At least in one study, it was shown that forested areas with complex stand structures could result in reflectance value saturation, making biomass estimation, for example, difficult within older forests (Lu et al., 2004). Some have also suggested that mathematical correction algorithms may be important for forest classification in areas with significant landscape relief (leading to the presence of shadows) or in areas with considerable bare soil (Zheng et al., 2007). Land cover types that are relatively homogeneous (pure pine stands and shrubland) generally allow high correlations to be observed between vegetation characteristics and spectral response, whereas land cover types with high spectral diversity (e.g., mixed species forest stands) generally result in low correlations. At least in one case (Mallinis et al., 2004), the spectral resolution and the spatial resolution (30 m *x* 30 m in most cases) of Landsat satellite imagery did not seem adequate for estimating the characteristics of forests that were patchy and fragmented. Therefore, stratification of forest cover types may be necessary prior to the use of any classification technique (Viana et al., 2012).

5. Conclusions

Over the last twenty years, Landsat satellite imagery has often been used in an effort to estimate stand-level forest characteristics. In this review we described some challenges that have been encountered in using Landsat satellite imagery for estimating stand-level forest characteristics, and described the techniques that have recently been employed to estimate these. In terms of stand-level forest characteristics, relatively speaking, average forest height, crown closure, and stand age were less frequently addressed than the others. Average stand age determination may require the use of synthetic data derived from Landsat satellite imagery, and stand age determination in tropical forests may be very challenging because young and old forests share similar spectral signatures, although object-based processes may be of value. However, often the concept of stand age is not appropriate in tropical forests that are basically uneven-aged. Attention has perhaps been placed more heavily on the estimation of forest biomass than other forest characteristics, and some have suggested that synthetic data (measures of brightness and wetness) may be necessary in estimating biomass levels as well. Several studies have noted that procedures for estimating continuous values at the extreme ends of the valid value spectrum tend to be less accurate and perhaps biased, and that ancillary data (in the case of timber volume) might be necessary.

Regression and *k*NN imputation techniques seem to be the most widely employed and are becoming mature and refined, although other techniques (e.g., neural networks, regression kriging) seem to hold promise and further attention should be applied to these as well. Empirical data still seems necessary for disentangling the relative differences between classification techniques, and for facilitating the ability to estimate certain forest characteristics. In most cases, estimation techniques predict forest characteristics poorly at small scales (the pixel) and very well at larger scales (40-100 ha). Further, more information is necessary to determine whether certain methods employed can be transferable to other geographic areas given varying vegetative, climatic, and topographic conditions, and varying objectives.

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CHAPTER 3

ESTIMATION OF PREMATURE FOREST AREAS IN GEORGIA USING U.S. FOREST SERVICE FIA DATA AND LANDSAT IMAGERY

1. Introduction

Pre-merchantable (or premature) tree area is considered valuable measurement for providing future opportunities for both commercial uses and conservation. Using knowledge about pre-merchantable tree area, bioenergy potential can be estimated, information on current merchantable stands can be better updated, and management schemes for young forests can be made more efficient, allowing forest managers and investors to better estimate market and investment value. Market value is the price for which an asset would sell on a competitive basis, and investment value is the value of an asset to a particular investor. Detailed and accurate information on pre-merchantable area can be useful fundamental data for anyone interested in estimating these values.

Ever-increasing computer power, geographic information system (GIS) software, and remote sensing data enhance the accessibility and accuracy of large-scale spatial data analysis in combination with inventory data such as the U.S. Forest Service Forest Inventory and Analysis (FIA) data. FIA data are often used to determine the extent, condition, volume, growth, and depletions of timber on the forest land of the United States (e.g., Rosson and Rose 2010). FIA personnel and their state partners collect forest inventory data on permanent sample plots within each state. FIA data are used as essential sources of information for various analyses of forest policies and programs. Using the extensive range of tools developed specifically for FIA data, information of interest can be obtained and selected by the public based on the research purpose and project hypotheses. In forestry, combining field inventory data with aerial photographs and satellite images has revolutionized traditional inventory processes. Typically, Landsat data have been used for parameter estimation or as auxiliary data in obtaining information about forest resources where such information was not available through field investigation (Reese et al., 2002; Mäkelä and Pekkarinen, 2004; Chen et al., 2007).

In this paper, we have two objectives. First, we examine and compare the tools for using FIA data such as Forest Inventory Data Online (FIDO) (U.S. Forest Service, 2012) and Forest Inventory and Analysis Database (FIADB) - Lite (Miles, 2008), and then pursue the estimation of, the amount (number and basal area) of “pre-merchantable trees” of which DBH is less than 12.7 cm (5 inches) in every county of the State of Georgia, using FIA data. Secondly, we try to classify and specifically identify “premature forest stands” in southeastern Georgia, where the age is 15 years or less, using data from Landsat Thematic Mapper (TM) based on the medium size spatial resolution of approximately 30-m pixel size with Maximum Likelihood Classification (MLC), regression analysis, and k-Nearest Neighbor (*k*NN) processes. The advantages and disadvantages of these methods are then compared. Finally, we examine the usefulness of Landsat imagery and various image processing classifiers for the purpose of premature stand identification based on the results of the classification processes.

2. Review of Approaches

2.1 The U.S. Forest Inventory and Analysis (FIA) program

The Forest Inventory and Analysis (FIA) program of the U.S. Forest Service provides information necessary for studying the transition of America's forests. The FIA program provides information that describes the current condition of forests, and enables one to evaluate whether forest management practices are sustainable in the long run. Over the last few decades, the FIA program has produced various reports on forest status and trends of United States forests, including species, size, growth, removals, and production of forestland by using field inventory plot data and remotely sensed imagery (U.S. Forest Service, 2012). Some details of these studies are presented below.

A fundamental aspect in the design of the FIA, double sampling for stratification, has been adopted to perform basic forest inventories (Chojnacky, 1998). Long ago, Neyman (1938) devised double sampling as a theory for sampling human population and Bickford (1952) adapted it to the FIA program in the northeastern United States. It was not easy to adapt the theoretical sampling design to actual field conditions; thus modifications and assumptions on the sampling design should be added to facilitate field sampling. In this approach of double sampling, a large first-phase sample from aerial photography is followed by a smaller second-phase ground sample. The first phase of double sampling includes photo-interpretation of aerial imagery using a dot-count method (Wynne et al., 2000). In the second phase, field plots are sampled to confirm that the photo-interpretation of the phase was correct. In general, double sampling for stratification is considered a simple but powerful way to describe most attributes for FIA inventories. The combined usage of field data and aerial photographs within a double sampling effort seems to enhance the ability to locate pre-merchantable stands of trees.

2.2 Estimation of forest parameters using remote sensing imagery and forest inventory data

Previous research on biomass estimation provides a foundation for methods used in this study to determine forest age structures and leaf area index (LAI). Zheng et al. (2007) mapped above-ground biomass (AGB) of forests by combining remote sensing imagery and forest inventory data. They used methods for measuring ecological parameters to process remote sensing images, and they developed regression models for estimation of biomass. In the field they measured topographic characteristics such as slope, aspect, and coordinates and forest parameters (Leaf Area Index, DBH, tree height and forest age). Zheng et al. (2007) selected 60 plots and observed parameters used for calculating AGB from 10 trees among 14 plots. They converted the Landsat Enhanced Thematic Mapper Plus (ETM+) raw digital numbers into radiance, and then using the “6S” model (Vermote et al., 1997) they used radiance to calculate the reflectance of each band. They then joined the images and produced a reflectance image for the whole study area. Topography can distort remote sensing signals, thus Zheng et al. (2007) used the Sun-Canopy-Sensor (SCS) sub-pixel removal method (Gu and Gillespie, 1998) to remove the shadow effect.

Zheng et al. (2007) used three different vegetation indices, simple ratio (SR) (Rouse et al., 1973; Tucker, 1979; Sellers, 1985), reduced simple ratio (RSR) (Brown et al., 2000), and normalized difference vegetation index (NDVI) (Rouse et al., 1973; Tucker, 1979; Jackson et al., 1983; Sellers, 1985) from atmospherically corrected ETM+ reflectance images. The RSR map with leaf area index (LAI) field measurements produced a LAI map based on statistical analysis, and Zheng et al. (2007) then produced an initial AGB map using the LAI map and forest stand age structure. They used vegetation indices, LAI, and forest stand age to make AGB estimation models for different forest types using stepwise regression analysis. The model with LAI and AGE captured 90% of the variance of the overall AGB. The various forest types, Chinese fir (*Cunninghamia lanceolata)*, conifer, broadleaf, and mixed forest, showed high correlation with specific combinations of LAI, AGE, NDVI, and SR. Zheng et al. (2007) developed a final AGB map with land cover information and derived age information. The forest age came from the initial AGB map that they attained from the LAI map and the relationship between AGB and age, which are too much complex steps. From their research we can consider a different way to estimate forest age structure with diverse combinations between LAI and AGB information, which means that it will be a simple method. Another option for the research could be the combined usage of diverse satellite sensors with different forest parameters such as crown size, with FIA age data to make this model compared in terms of accuracy.

Landsat TM data is captured over seven bands of electromagnetic energy. The spatial resolution of all bands is 30 m except that of band 6, which is 120 m. Turner et al. (1999) researched the relationships between LAI and Landsat TM Spectral Vegetation Indices (SVI) and they found out a strong general relationship with SVI’s increasing up to LAI values of 3 to 5 with relatively high-level of squared R values, all of which are over 0.5. Based upon the strong relationship between SVI and LAI, we can gain the ability to map and monitor LAI across large-scale area using remote sensing imagery fast and accurately, which provides crucial information to estimate biomass and age structure

Lu et al. (2004) researched the relationship between forest stand parameters and Landsat TM spectral responses in the Brazilian Amazon Basin. They produced summary statistics of forest parameters of above-ground biomass (AGB), basal area (BA), average stand diameter (ASD) and average stand height (ASH) from field data in the three study areas of Altamira, Bragantina, and Pedras from June to July in 1991. They employed TM images in July 1991 for Altamira and Pedras and for June 1994 for Bragantina in this research. Lu et al. (2004) did geometrical rectification and radiometric and atmospheric correction on acquired remote sensing data and calculated vegetation indices (Simple ratio, Normalized vegetation indices, Complex vegetation indices, and Image transform). They linked geometrically rectified sample data to individual TM bands or the vegetation indices. They connected spectral responses with stand parameters using a Pearson's correlation coefficients analysis, and measured the coefficients between two variables. Tree species composition, forest stand structures, and associated canopy influenced vegetation reflectance, although the sites had similar biomass. To make this approach more applicable, we would want to determine how the different characteristics such as age structure are illustrated by vegetation reflectance. For example, if we can define the age structure with only the vegetation reflectance given constant biomass, we can expect to estimate pre-merchantable stands more easily using the relationship.

The results by Lu et al. (2004) showed that single Landsat TM band 5 and linear transformed indices such as PC1 (the first component in a principal component analysis), KT1 (brightness of the tasseled cap transform), and albedo strongly correlate with forest stand parameters when using Pearson's correlation coefficients. The relationship between many vegetation indices using Landsat TM band 4 and Landsat TM band 3 data and selected forest parameters was not strong. But, the vegetation indices with Landsat TM band 5 showed relatively high correlation with forest parameters, even in a complex forest structure. For example, in Altamira the correlation coefficients between TM5 and AGB, BA, ASD, and ASH were -0.627, -0.576, -0.794, and -00.851. Through the study by Lu et al. (2004), we discovered that the best spectral data forms for detecting forest stand parameters were Landsat TM band 5, PC1, KT1, albedo, and MID57 (the addition of the middle infrared Landsat TM bands). The topographic variation in a study area can become an issue. Among three study areas, the topographic variation in two study areas is flat and the other is a mixture of flat and rugged terrains. Thus, this research area was mainly flat and the authors did not use enough elevation variation. The complexity of forest structure can weaken the relationship proposed here; thus, based on the results of various topographic conditions, we should consider modification of coefficients and use of additional independent variables of the spectral bands sensitive to biophysical environments. One strong point of this research is that Lu et al. (2004) collected large amounts of data on all saplings, seedlings, and herbaceous vegetation in subplots. We can use this research as a guide for using suitable TM bands and vegetation indices and as the basic framework of the relationship between satellite data and forest stand parameters. This will provide a variety of options for selection of forest parameters for the purpose of verification and more accurate delineation of specific forest structure such as pre-merchantable stands.

Remote-sensing based biomass estimation also can involve various methods and data types. For example, Thenkabail et al. (2004) used IKONOS data for Biomass estimations and carbon stock calculations. At the landscape level, multi-date IKONOS data showed an overall accuracy of 88-92% given the ground truth data and based on the fact that IKONOS provides fine spatial resolution (1m panchromatic and 4m multispectral 3-band images) with this high accuracy of estimation, we can consider this approach suitable for local-scale biomass mapping. As remote sensing technologies, The Indian Remote Sensing Satellite (IRS) –1C Wide Field Sensor (WiFS) and Advanced Very High Resolution Radiometer (AVHRR) are employed for per-pixel level by the methods based on coarse spatial-resolution data, which is larger than 30 m (Barbosa et al., 1999; Dong et al., 2003) and those approaches are appropriate for larger scale areas such as a national area based on the large spatial resolution (Lu, 2006). Barbosa et al. (1999) obtained the uncertainty of 51% for the burned biomass and Dong et al. (2003) compared remote sensing and inventory estimates of biomass carbon pool using a *t*-statistic and the null hypothesis was rejected with *p*-value less than 0.05. In general, we can conclude that the spatial resolutions of each satellite are crucial factors to decide which scale of area will be best for the satellite images. Based on the comparisons of various satellite data used in biomass mapping, Landsat TM/ETM might be suitable for regional scale areas such as counties based on their medium spatial resolution of approximately 30-m pixel size (Lu, 2005).

In this research, we tried to estimate a specific trait of forest stands, the premature forest stage. Through this research we assessed if the estimation of such a specific trait can be achieved with acceptable accuracy results. We also assessed several image processing classifiers which are used for forest cover classification in order to determine which image processing classifier among them will be more suitable in the estimation of premature forest stand in terms of accuracy results and its application. We compared the advantages and disadvantages of each image processing classifier for the estimation of young forest areas.

3. Data and Materials

The combination of systematic and random sampling is fundamental to the design of the FIA program (Chojnacky, 1998). Each plot and subplot has various features including ownership, forest type, stand age, stand origin, site productivity class, site index and base age, land use class, basal area per area unit, treatment opportunity class, volume, growth, mortality and removals and expansion factors for area. FIA personnel also record multiple variables at the species level. These are DBH, total height, quality class, crown ratio and crown class, damage and its cause. The data we used in this research about the estimation of pre-merchantable trees we obtained from 2008 FIA permanent sample plot surveys of Georgia.

In the following study, we employed a Landsat Thematic Mapper (TM) 5 image acquired on 17 July, 2011 with path 017 row 038 which are southeastern parts of Georgia. We used all seven TM band. The resolution of 6 120 m × 120 m was resampled to 30-m pixels after February 25, 2010. Since we used only a single scene at a time and we were not grouping signatures from 2 or more scenes, no additional processing for Landsat imagery was conducted (Song et al., 2001). In addition, we made training data sets which are used as standard data sets for predicting land classes and also made reference data which are kind of ground truth data used for checking accuracy tests separately using time-series aerial photos and field inventory data. Specifically, for MLC, training data sets of polygons and points depicting premature forests were obtained from FIA plot boundaries and verified recently acquired aerial photographs by visual inspecting.

4. Methods

4.1 Study area

We have two different ranges of study areas according to two objectives. To meet the first objective, to examine the amount of pre-merchantable trees using tools for the use of FIA data, 159 counties of Georgia were selected as the study area. To meet the second objective, to classify premature forest stands, of which the age is 15 years or less using Landsat imagery of southeastern Georgia, the study area includes parts of 34 counties falling within the area covered by the Landsat image, namely, Appling, Atkinson, Bacon, Ben Hill, Berrien, Brantley, Bryan, Bulloch, Camden, Charlton, Chatham, Clinch, Coffee, Dodge, Effingham, Emanuel, Evans, Glynn, Irwin, Jeff Davis, Johnson, Lanier, Laurens, Liberty, Long, McIntosh, Montgomery, Pierce, Tattnall, Telfair, Toombs, Treutlen, Ware, Wheeler (Figure 3.1).

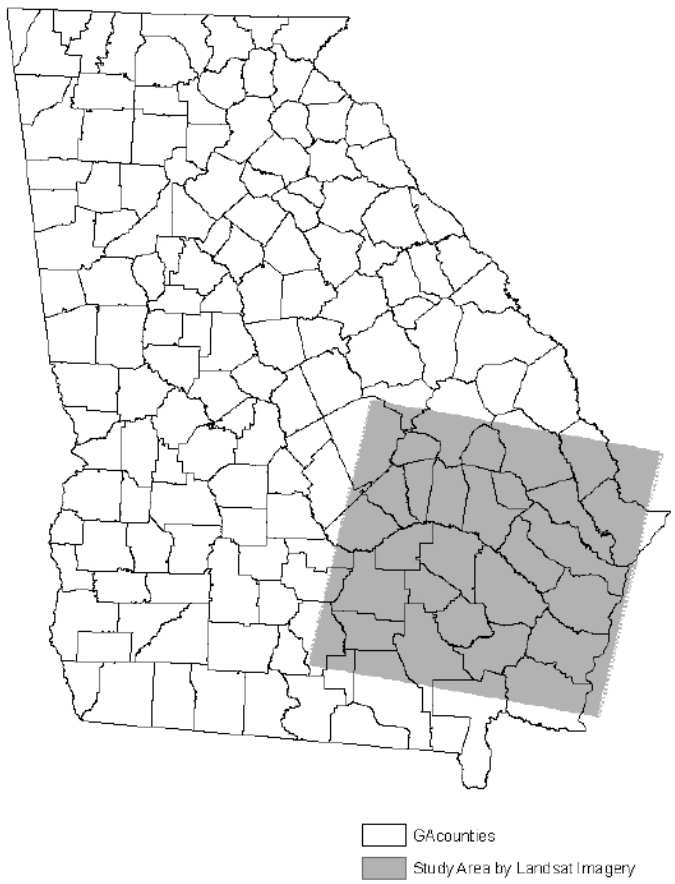

Figure 3. 1: Study area. For the first objective, the study area includes all counties of Georgia including white and gray and for the second objective, gray colored areas were studied.

4.2 Estimation of the number and basal area of pre-merchantable trees on timberland of Georgia using FIA data

Pre-merchantable trees are defined as trees whose DBH is less than 5 inches (12.7 cm). Thus, in the estimation of pre-merchantable tree area using FIA data, DBH was utilized as the standard variable for classification. We used Forest Inventory Data Online (FIDO) (U.S. Forest Service,

2012) to generate tables of numbers of pre-merchantable trees in Georgia. In the use of FIDO, we can select the following information in a web-based application:

- Each county of Georgia
- The number of trees as attribute of interest
- Filters for pre-merchantable trees – DBH less than five inches
- Classification variables to be used for pages, rows and columns

From the information listed above, FIDO produced tables of numbers of pre-merchantable trees with diameter classes by each county of Georgia. Employing the relevant regression equations we calculated basal area using the average DBH classes and number of trees in each county.

FIADB-Lite (Miles, 2008) can generate estimates of forest land area and tree biomass, volume, growth, removals, and mortality. With modification of queries for pre-merchantable stand areas in counties of Georgia, we can estimate various variables depending on the research objectives (Table 3.1).

Table 3.1: MS-access SQL query for pre-merchantable trees

```
SELECT
    ([COND].[STATECD]*1000+[COND].[COUNTYCD]) AS StCntyID,
   Sum([EXPCURR]*[CONDPROP_UNADJ]*[ADJ_EXPCURR]) AS [Area of forestland-
acres]
FROM
   POP_EVAL_GRP INNER JOIN ((PLOTSNAP INNER JOIN COND ON
PLOTSNAP.CN=COND.PLT_CN)
 INNER JOIN TREE ON (COND.PLT_CN=TREE.PLT_CN) AND
(COND.CONDID=TREE.CONDID)) ON POP_EVAL_GRP.CN=PLOTSNAP.EVAL_GRP_CN
WHERE
   ((([COND].[COND_STATUS_CD])=1)) and [POP_EVAL_GRP].[EVAL_GRP]=132008 and
([tree].[dia] < 5)
GROUP BY
   ([COND].[STATECD]*1000+[COND].[COUNTYCD]);
```

4.3 Estimation of premature forest stands using Landsat imagery

To estimate premature forest stands using Landsat imagery, age structure was used as a standard variable. We used 15 years or under as the standard age for premature forest stands, which can correspond to premature stands. Three classifiers, MLC, linear regression analysis, and *k*NN, were employed to classify premature forest areas. Our premise is premature forest differs in spectral reflectance from mature forest and its background of grass and bare land.

A sufficient number of samples per the class of map are required for accuracy assessment to be a statistically valid representation. For an error matrix, a multinomial distribution can be employed to produce the suitable number of sample size (Congalton and Green, 2008). Based on the procedure for developing the proper sample size (Tortora, 1978), we calculated the appropriate sample size to be 126 with a desired precision of 0.10 and the sample size to be 87 with a desired precision 0.12. Therefore, we assumed a sample size of 100 for each class, which means the desired precision should range from 0.12 to 0.10. Finally, for accuracy tests, we used 100 reference data points which corresponds to premature forest areas and 100 additional reference data points for others.

4.3.1 Maximum likelihood classification

MLC is one of the most powerful image processing classifiers and is commonly used for estimating forest parameters. The algorithm used by MLC is based on two principles of: (1) the cells in each class sample show normal distribution, (2) Bayes' theorem of decision making (Lillesand et al., 2008). Based on the assumption that a class sample is normally distributed, the mean vector and the covariance matrix can characterize a class. Then, the MLC method calculates a probability for a given pixel from a specific class of training data set based upon mean and variance/covariance of pixel reflectance values (or digital numbers) and, then the algorithm of MLC assigns the pixel to the class of highest probability (Richards, 1999). Here, I classified the Landsat image into 6 classes, which are premature forest, mature forest, bare land, grass, water, and urban as training data, which are standard land classes. However, the accuracy assessment involves only 2 classes (premature forest, and the aggregation of all others). MLC was conducted using ArcGIS.

4.3.2 Regression analysis

Ordinary Least Squares (OLS) regression also was used to classify premature forest-stand areas. The OLS minimizes the sum of squared differences of the observed data value from the estimated. The general equation becomes:

$$G = \alpha + \beta i \ (Xi) + \varepsilon \qquad \text{Equation 1}$$

where, G is dependent variable which is stand age, *Xi* is an independent variable for the reflectance value of Landsat Bands 1 to 7 (*i*) at each grid cell within a Landsat image, βi is a coefficient for each Landsat band and ε is residual error. The *Zonal Statistics* tool in ArcGIS was used to calculate mean spectral values of each band in the Landsat imagery for each stand (polygon) having the same age structure.

4.3.3. k- Nearest Neighbor

Finally, the *k*NN method, with training datasets representing age structure, was applied to the Landsat imagery. In the same method as regression analysis, I used the *Zonal Statistics* in ArcGIS tool to calculate mean spectral values of each band of the Landsat imagery. To impute the *k*NN method, I used “yaImpute” as the *k*NN algorithm (Crookston and Finley, 2008). In the yaImpute program, the *Y* variable is the stand age and the *X* variables are associated with the Landsat imagery. Therefore, the training dataset is composed of Landsat pixels with corresponding stand ages, and target observations become Landsat pixels without an age assigned. As the method for finding nearest neighbor, I used randomForest (Crookston and Finley, 2008), which uses no weighted Euclidean distance among the various options, and *k* was set as 1 in our research.

4.3.4 Method for accuracy assessment

For assessing the accuracy of classifications results, we developed an error matrix (confusion matrix or a contingency table) which is the most widely and commonly used (Lillesand et al., 2008; Congalton and Green, 2008). Based on the error matrix, we calculated the overall accuracy by dividing the sum of the number of pixels that were correctly classified by the total number of samples (Reference data). We also derived the percentage correct allocation for premature stands and mature stands from the user's and producer's points of view (Story and Congalton, 1986). The producer's accuracy refers to the probability that a certain land-cover of an area on the ground is classified as such and indicates possible errors of omission, while the user's accuracy indicates the probability that a pixel labeled as a certain land-cover class in the map is really this class and indicates errors of commission. Additionally we utilized the kappa coefficient (κ) of agreement as a measure of classification confidence because it indicates agreement beyond chance agreement (Rosenfield and Fitzpatrick-Lins, 1986).

The equations for the kappa analysis are presented here based on the procedures described in Congalton and Green (2008). Let us assume we have *n* samples in k^2 cells, and each sample is simultaneously assigned to one of *k* categories in both the map and the reference data set. Let n_{ij} represent the sample number in category *i* for the map and category *j* for the reference data set. Then, let

$$n_{i+} = \sum_{j=1}^{k} n_{ij}$$

be the samples numbers classified into category *i* in the classification by remote sensing imagery, and

$$n_{+j} = \sum_{i=1}^{k} n_{ij}$$

be the samples numbers classified into category *j* in the reference data set. Then, overall accuracy can be computed like this:

$$\text{overall accuracy} = \frac{\sum_{i=1}^{k} n_{ii}}{\text{n}}$$

Producer's accuracy can be computed as follows:

$$\text{producer}'\text{s accuracy } j = \frac{n_{jj}}{n_{+j}}$$

and the user's accuracy can be computed as follows:

$$\text{user}'\text{s accuracy } i = \frac{\text{n}_{\text{ii}}}{n_{i+}}$$

In addition, the kappa coefficient (κ) can be calculated by

$$\kappa = \frac{n\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{i+}\, n_{+i}}{n^2 - \sum_{i=1}^{k} n_{i+}\, n_{+i}}$$

5. Results and Discussion

5.1 Estimation of pre-merchantable trees in each county of Georgia using FIA

Using the FIDO and FIA data method proposed in section 4.2, we estimated the number of pre-merchantable trees by diameter classes, the number of all pre-merchantable trees, and the number of all trees. With those values we calculated the number of pre-merchantable trees per county area and the proportion of pre-merchantable trees to all trees on timberland in each county of Georgia (Table 3.2). In addition, with relevant equations regarding the relationship between DBH and basal area, we calculated the basal area of pre-merchantable trees by different DBH classes, total basal area of pre-merchantable trees, and total basal area of all trees. With those values, we calculated the basal area of pre-merchantable trees per county area and the percentage of pre-merchantable trees on timberland in each county of Georgia (Table 3.2, Figure 3.2).

The FIDO estimates indicated Clinch County has the highest number of pre-merchantable trees, and the percentage of pre-merchantable trees ranges from 50% to 89% with an average 76%. Webster County showed highest percentage of pre-merchantable trees against all number of trees. The percentage of basal area of pre-merchantable trees ranges from 7.6% to 37% against all trees' basal area with an average of 21% on timberland in each county. Stewart County showed the highest proportion of pre-merchantable tree basal area among all Georgia counties. Seminole County had the lowest value of pre-merchantable tree basal area.

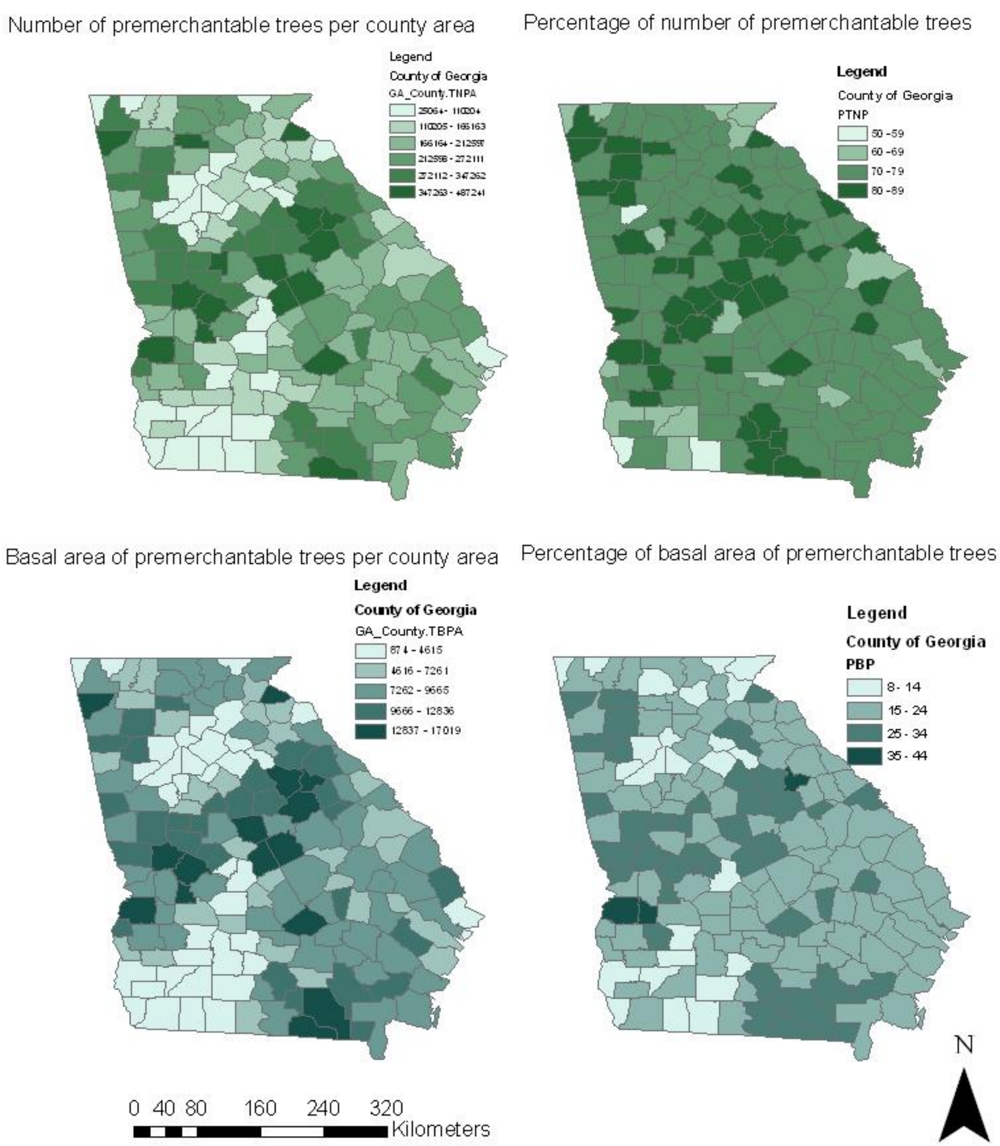

Figure 3.2: Pre-merchantable trees in counties of Georgia

Table 3.2: Number of pre-merchantable trees in selected counties of Georgia

County	Number of trees by diameter classifications		Total number of pre-merchantable trees	Total number of all trees	% of number of pre-merchantable trees against number of all trees
	1.0-2.9 in	3.0-4.9 in			
Appling	78,732,473	26,117,418	104,849,891	146,604,980	72
Atkinson	43,200,057	17,100,519	60,300,576	83,909,689	72
Bacon	33,398,882	21,641,749	55,040,631	81,697,884	67
Ben Hill	27,889,056	18,961,622	46,850,678	71,082,944	66
Berrien	107,612,574	26,493,379	134,105,953	164,572,981	81
Bleckley	33,844,304	9,429,931	43,274,235	56,535,354	77
Bryan	55,456,610	23,460,625	78,917,235	115,227,090	68
Bulloch	124,304,467	32,833,902	157,138,369	210,882,587	75
Camden	106,823,729	36,531,255	143,354,984	198,989,944	72
Charlton	100,038,850	47,233,166	147,272,016	203,098,614	73
Chatham	29,363,032	14,003,908	43,366,940	60,795,379	71
Clinch	160,427,737	85,908,689	246,336,426	342,452,999	72
Coffee	90,668,408	30,230,750	120,899,158	158,099,360	76
Dodge	94,626,778	28,382,073	123,008,851	161,154,705	76
Emanuel	139,860,274	34,266,600	174,126,874	230,907,947	75
Evans	31,460,805	6,716,484	38,177,289	51,439,985	74
Glynn	53,257,516	19,846,714	73,104,230	95,680,328	76
Irwin	41,999,883	9,776,132	51,776,015	65,784,736	79
Jeff Davis	58,157,110	22,557,147	80,714,257	111,689,082	72
Johnson	46,825,889	9,468,638	56,294,527	79,376,895	71
Lanier	38,433,749	16,827,458	55,261,207	68,064,791	81
Laurens	155,595,789	45,749,569	201,345,358	260,731,212	77
Liberty	76,117,400	18,045,718	94,163,118	129,062,960	73
Long	114,497,332	28,881,493	143,378,825	180,897,274	79
McIntosh	73,080,390	16,238,762	89,319,152	118,601,562	75
Montgomery	55,516,211	18,009,957	73,526,168	92,650,910	79
Pierce	39,170,167	20,280,572	59,450,739	80,654,426	74
Tattnall	59,076,482	31,972,145	91,048,627	125,671,650	72
Telfair	140,614,750	40,133,246	180,747,996	217,852,224	83
Toombs	58,642,623	15,323,364	73,965,987	96,043,852	77
Treutlen	29,720,783	8,905,644	38,626,427	54,878,671	70
Ware	171,371,430	72,967,485	244,338,915	307,585,157	79
Wheeler	45,102,375	14,407,966	59,510,341	80,914,489	74

Table 3.3. Basal area (BA) (ft^2) of pre-merchantable trees in selected counties of Georgia

County	BA by tree diameter classification		Total BA of pre-merchantable trees	Total BA of all trees	% of the BA of pre-merchantable trees against the BA of all trees
	1.0-2.9 in	3.0-4.9 in			
Appling	1,717,628	2,279,110	3,996,738	21,868,160	18
Atkinson	942,452	1,492,260	2,434,712	10,078,836	24
Bacon	728,630	1,888,546	2,617,176	12,262,848	21
Ben Hill	608,428	1,654,667	2,263,095	10,706,077	21
Berrien	2,347,676	2,311,918	4,659,594	15,942,268	29
Bleckley	738,347	822,893	1,561,241	7,481,654	21
Bryan	1,209,841	2,047,268	3,257,109	20,808,813	16
Bulloch	2,711,826	2,865,218	5,577,044	26,683,626	21
Camden	2,330,466	3,187,863	5,518,330	27,969,625	20
Charlton	2,182,448	4,121,755	6,304,203	25,810,504	24
Chatham	640,584	1,222,037	1,862,621	11,921,612	16
Clinch	3,499,892	7,496,736	10,996,627	41,457,065	27
Coffee	1,978,022	2,638,056	4,616,078	19,751,422	23
Dodge	2,064,378	2,476,733	4,541,111	20,708,163	22
Emanuel	3,051,192	2,990,241	6,041,432	29,331,847	21
Evans	686,349	586,107	1,272,456	8,707,411	15
Glynn	1,161,866	1,731,904	2,893,770	12,273,257	24
Irwin	916,269	853,104	1,769,374	9,273,550	19
Jeff Davis	1,268,756	1,968,427	3,237,182	14,643,467	22
Johnson	1,021,554	826,271	1,847,825	10,883,032	17
Lanier	838,471	1,468,431	2,306,902	7,732,909	30
Laurens	3,394,478	3,992,290	7,386,768	31,980,782	23
Liberty	1,660,577	1,574,742	3,235,319	22,061,455	15
Long	2,497,874	2,520,315	5,018,188	21,390,239	23
McIntosh	1,594,322	1,417,059	3,011,381	15,022,435	20
Montgomery	1,211,142	1,571,621	2,782,763	11,207,396	25
Pierce	854,536	1,769,764	2,624,300	11,387,487	23
Tattnall	1,288,813	2,790,017	4,078,830	17,843,844	23
Telfair	3,067,651	3,502,188	6,569,839	21,834,178	30
Toombs	1,279,347	1,337,178	2,616,525	12,112,052	22
Treutlen	648,389	777,142	1,425,531	9,096,455	16
Ware	3,738,639	6,367,435	10,106,074	30,635,798	33
Wheeler	983,953	1,257,297	2,241,250	14,009,879	16

The results from FIDO do not show big differences compared to FIADB-Lite, but we detected small differences between the values from U.S. Forest Service FIDO and FIADB-Lite and it is inferred that FIDO has more recently updated data than FIADB-Lite. Therefore, if data are detailed enough for the purpose of this research project, we can use FIDO to easily access FIA data. The percentage of the number of pre-merchantable trees was relative higher than the percentage of basal area of pre-merchantable trees in every county of Georgia. We inferred that since pre-merchantable trees are young and have small DBHs, the proportion of basal area of pre-merchantable trees is relatively lower than the proportion of the number of pre-merchantable trees to all trees. This is reasonable in that young plantations have lots of trees, but their stand basal area is not relatively high.

5.2 Estimation of premature forest area using MLC, regression analysis, and kNN in southeastern Georgia

MLC was applied to the Landsat images using ArcGIS and 6 classes (premature forest, mature forest, bare land, grass, water, and urban) were developed (Figure 3.3). Based on the classified image, an error matrix for premature forest stands and the other areas was developed (Table 3.4). Among 100 reference data of premature stands area, 69 points were classified into premature stands and 31 points were misclassified. Among 31 misclassified points, 22 points were misclassified as bare land and 8 points were misclassified as grass. Thus, premature stands had a 69% producer’s accuracy and a 92% user’s accuracy. Among 100 reference data of other areas, only 6 points were misclassified as premature forest area. Thus, other areas except premature stands area showed a 94% producer's accuracy and a 75% user's accuracy. The overall accuracy was 82 % and the corresponding kappa coefficient was 0.63.

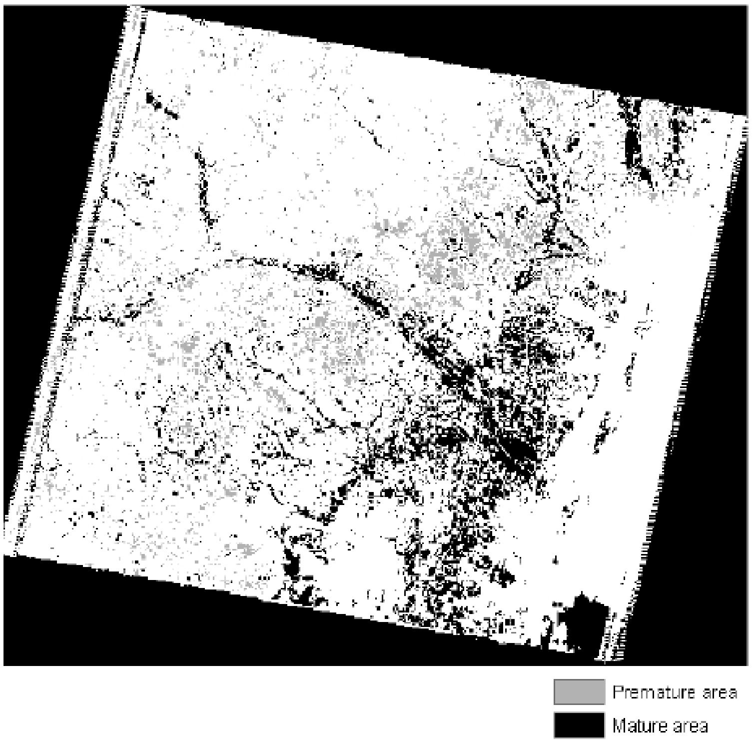

Figure 3.3: Premature forest area and mature forest area derived from Maximum Likelihood Classification

Table 3.4: Error matrix for premature forest stands area and the others by MLC

	Reference data		
Classification	Premature forest	Others	Row Total
Premature forest	69	6	75
Others	31	94	125
Column Total	100	100	200

Producer's accuracy		**User's accuracy**	
Premature forest	69	Premature forest	92
Others	94	Others	75

In the estimation of premature forest areas, the error matrices indicate that the overall accuracy of MLC performed relatively well. Although, if we investigate some problems in it most errors came from confusion with bare land and some errors came from grass. Foody et al. (1996) found that a large proportion of the errors using MLC were derived from misallocations between neighboring classes and they noticed that 83% of the observed errors in object-based classifications were between neighboring classes. Although our research is based on pixel-based classifications, bare lands and grass areas can be regarded as neighboring classes to premature stands in that it could be previous stages of premature stand, so it seems to be that some errors came from the confusion from such neighboring classes. We infer that in the very young forest areas the information of spectral reflectance includes the signal of soil of grass to young trees.

Such signals mixed with spectral reflectance of soil or grass in premature forest areas seem to be less distinctive from bare lands or grass. Even when we initially locate the bare land, grass and premature forest areas as training data, it is not easy to classify the classes using only the time-series aerial photos.

One notable point is there is only one reference point of premature forest area that was misclassified as mature forest area using MLC. When we created training data of premature forest area, we tried to select obvious premature forest, which means relatively young stands even among premature forest areas. Thus, it seems that such misallocation of premature forest area reference points as mature forest area was minimized. If we can create training data more evenly ranging from stand year 1 to 14, we realize some errors with premature forest areas being misclassified as forest. One more point to be considered is the acquired time gap of almost one year between the date when the Landsat imagery was taken and the aerial photos that were used to classify premature areas. Since bare land and grass are temporally dynamic classes, such a time gap seems to induce the classification errors between bare land (or grass) and premature forest area. In the classification for other areas except premature forest areas, only 6 reference data points of other areas were misclassified into premature stands area, which makes producer's accuracy for other classes relatively high, resulting in the overall accuracy of MLC relatively high although the producer's accuracy for premature stands was not so high. This also makes user's accuracy for premature forest areas high, which means it is a credible classification map for premature forest areas in perspective of map users.

Although many reference points of other classes (94) were classified correctly, the user's accuracy for other areas was not as high due to misclassification in premature forest areas reference points as other areas. If one has interests in accuracy for classification regarding both premature forest stands and other classes, MLC might be a most suitable option. Foody et al. (1996) found dividing the young forests by the successional pathway increased the accuracy of classification. Foody et al. (1996) also found that the young forest group showed diversity in its composition and spectral response. Such various traits in young forest areas appear to make the range of spectral reflectance's signals diverse and influence misallocations in our error matrix. Thus, more detail classification in age ranges, succesional pathway, and general species will make training datasets more distinctive and helpful for acquiring higher accuracy results in further research. It is likely that the most crucial factor influencing the algorithm used for MLC is creating accurate and distinctive training data that cover the entire range of spectral reflectance of a class. When we have such training data, the classification results may be more credible and can be employed for making an effective forest management scheme. MLC seems to be a useful method when used with remotely sensed imagery to search for young forest areas.

Regression analysis has been used most commonly with field inventory and satellite imagery for the estimation of forest stand-level characteristics based on for less data than other methods such as *k*NN (Kim et al., 2012). We used the statistical software R and the result of regression analysis was presented in Table 3.5.

Table 3.5: Parameter estimates for regression model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	80.29091	35.77081	2.245	0.0486*
band1	1.75948	0.99215	1.773	0.1066
band2	-0.75192	3.31755	-0.227	0.8253
band3	-3.10559	2.10043	-1.479	0.1701
band4	-0.77636	0.3128	-2.482	0.0324*
band5	0.67719	0.29289	2.312	0.0434*
band6	-0.50899	0.25319	-2.01	0.0721.
band7	-0.04313	0.02517	-1.713	0.1174

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.22 on 10 degrees of freedom

Multiple R-squared: 0.9019, Adjusted R-squared: 0.8332

F-statistic: 13.13 on 7 and 10 DF, p-value: 0.0002588

Therefore, the multiple regression equation that was developed to estimate premature forest areas was:

$$G = 1.76\ X_1 - 0.75\ X_2 - 3.11\ X_3 - 0.78\ X_4 - 0.68\ X_5 - 0.51\ X_6 - 0.04\ X_7$$

where, G = Stand age and X_i = ith TM band of Landsat imagery

The results of stand age which are applied to Landsat imagery are presented in Figure 3.4. Based on these results, we developed an error matrix for the estimation of premature forest area (Table 3.6). Among the 100 reference data points corresponding to premature forest areas, only 54 reference points were correctly classified into premature forests area, and 46 points were wrongly classified into mature forest based on the classified area by regression analysis. Therefore, this process had a 54% producer's accuracy and a 57% user's accuracy for premature forests. Among the 100 reference data points corresponding to other areas, 40 points were misclassified as premature forests and 60 points were classified correctly as other areas. Thus, the other areas showed a 60% producer's accuracy and a 57% user's accuracy. The overall accuracy of this classification process was only 57%. We also had a kappa coefficient 0.14, which suggests a poor agreement.

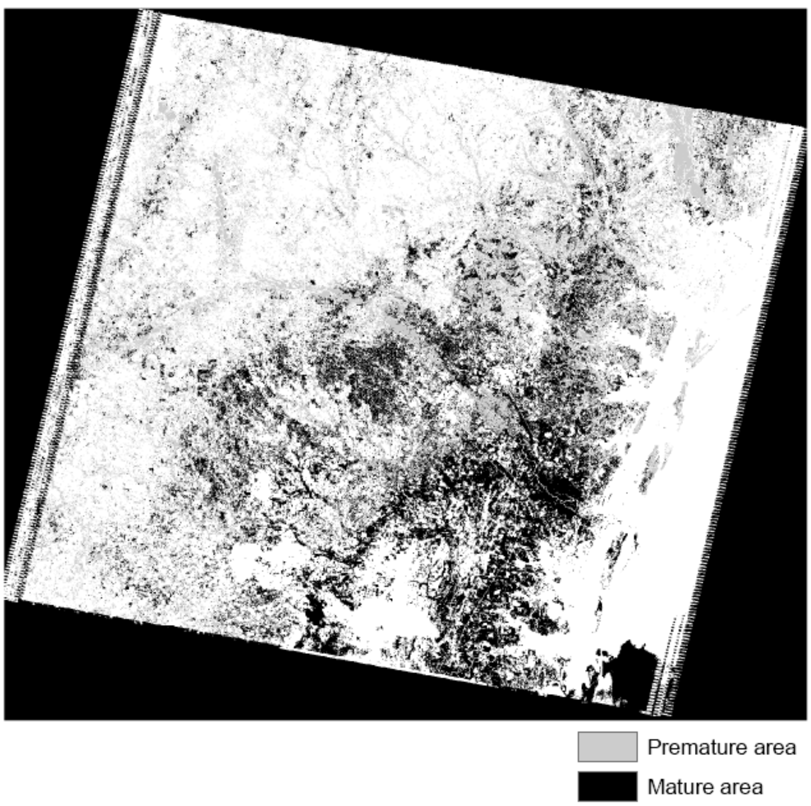

Figure 3.4: Premature forest area derived from regression analysis

Table 3.6: Error matrix for premature forest stand area and the other areas by regression analysis

	Reference data		
Classification	Premature area	Others	Row Total
Premature forest	54	40	94
Others	46	60	106
Column Total	100	100	200

Producer's accuracy		**User's accuracy**	
Premature forest	54	Premature forest	57
Others	60	Others	57

Although the relationship developed was statistically significant with an R^2 of 0.9, the regression analysis did not produce suitable accuracy results from the point of view of the error matrix (Table 3.6). One issue to note is that the misclassified data in reference points of premature forest areas involved many points that ranged in forest age from 16 to 25, which are very close to the threshold year 15. It means that such errors which are observed are located near a border line of premature stands and those errors are not so severe. Such misallocations near the boundary line between premature and mature forest areas seem to make each producer’s accuracy relatively low. Therefore, each user’s accuracy for premature forest areas and others was so low, which means the classified map of premature areas and other areas are not so much credible for users.

In using regression analysis one of the problems related to misallocations near the boundary year 15, between premature and mature forests, can be derived from the fact that we did not have enough training data to cover the both entire Landsat imagery and the entire time period for premature forest areas, although regression analysis can be run with a limited number of training data. The training data sets were mainly located in northern areas of Landsat imagery. If we can have enough training data we can represent the entire Landsat image which is used for our research and cover the entire time period of premature forest, the accuracy results might be enhanced.

Also, it is likely that linear regression analysis is not suitable for classifying young forest areas because their relationship between premature age and reflectance seems to be less linear. Brown and Lugo (1990) researched the relationship between biomass and forest age and found that there is a rapid increase in biomass in young forest areas. Such rapid increase in young forest areas appears to make spectral responses more varied. Consequently, it can result in slightly increased coefficient values, making a fitted line more upward. Thus, non-linear regression analysis might be considered to test if it is more suitable for the estimation of premature forest areas. Because we tried to use major and general techniques which were used to estimate forest structure, we employed a linear regression. However, in our case to classify premature forest area and mature forest area, logistic regression might be considered, and it will be a next further step which is essentially required.

In addition, we only made regression analysis between each band of Landsat imagery and age structure. Lu et al. (2004) showed that not only single-band but also some linear transformed indices are strongly correlated with forest stand parameters when using Pearson's correlation coefficients. They also found the vegetation indices with TM5 showed relatively high correlation with forest parameters. Thus, it is strongly suggested that a diverse combination of selected bands be tested, and we might find better band combinations to produce more accurate results for the estimation of forest stand age. Although it did not produce high accuracy results, we cannot conclude that linear regression analysis is not suitable for estimating all ranges of age structures because we had a statistical result which is significant and strong (R^2 equals 0.9), but it seems that linear regression can be not suitable for classifying just young forest areas.

The results for estimating premature forest stands using the *k*NN method are presented in Figure 3.5. Among the 100 reference points corresponding to premature forest stands areas, 74 points were classified correctly and only 26 points were misclassified. For the 100 reference points corresponding to other areas, 48 points were classified into the correct category. Therefore, the overall accuracy was 61% and the kappa coefficient was 0.22, which means that the *k*NN method showed a poor accuracy result. We had user's accuracy 59% area and producer's accuracy 74% for premature stands area. We can see that 41% of premature stands area reference data was misclassified and 26% of samples which is classified as premature stands area were wrong. It is also shown that other areas had 48% producer's accuracy and 65% user's accuracy.

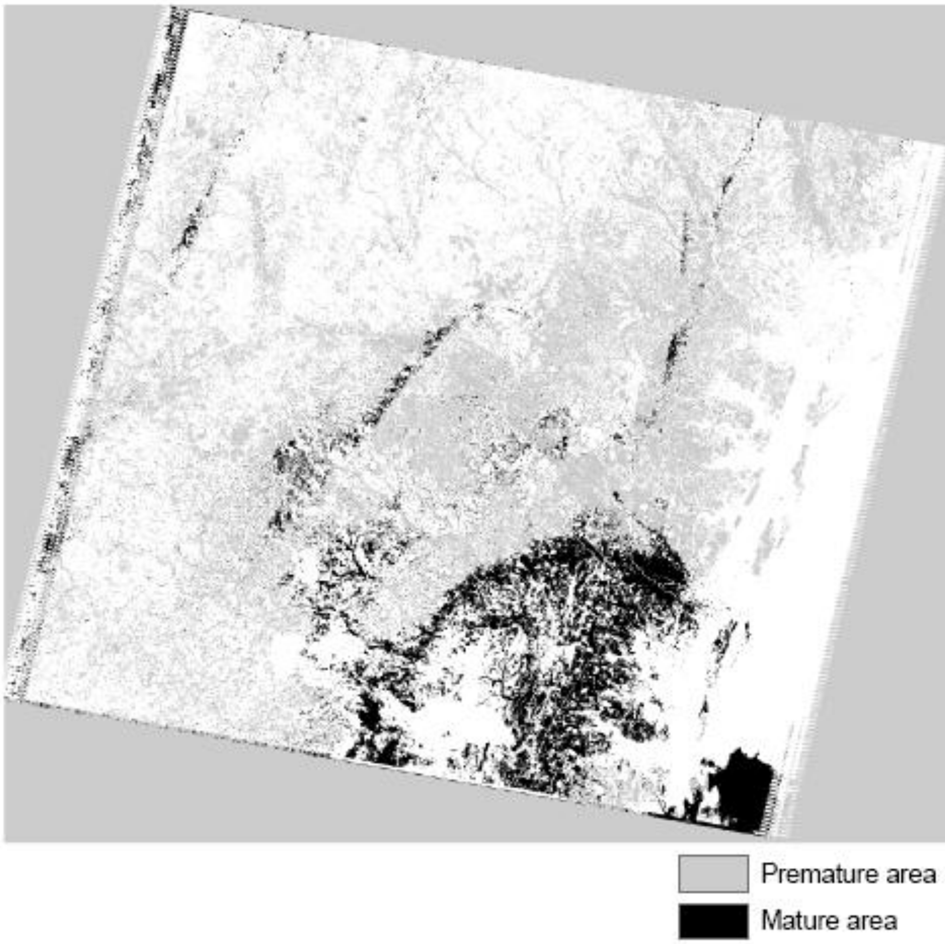

Figure 3.5: Premature stand area derived from k-nearest neighbor method

Table 3.7: Error matrix for premature forest stand area and the other areas by kNN method

	Reference data		
Classification	Premature forest	Others	Raw Total
Premature forest	74	52	126
Others	26	48	74
Column Total	100	100	200

Producer's accuracy		**User's accuracy**	
Premature forest	74	Premature forest	59
Others	48	Others	65

Using *k*NN we had a higher value in producer's accuracy for premature forest areas than other image processing classifiers. However, relatively other areas did not show a high value of producer's accuracy (48%). The user's accuracy for other areas is higher than the user's accuracy for premature forest areas. Basically, we used a training dataset ranging from 6 to 15 years for premature stand area and 16 to 30 years for other areas, which means the range of training dataset for other areas is relatively limited considering the whole age range of mature forest areas is much wider than that of premature forest area. It is likely that such limited ranges of training data in mature forest areas possibly made some reference plots of mature forest areas misclassified as premature forest stand areas, causing user's accuracy for premature forest areas and producer's accuracy for other areas to be relatively low. This matter seems to make the overall accuracy for *k*NN (61%) relatively low. For efficient non-parametric mapping, the availability of sufficient plot samples is essential over a large area (Tokola et al., 1996; Labrecque et al., 2006). Although the *k*NN method creates reasonable estimation results for premature forest areas, here it is confirmed that without enough plot samples in spatial extent of Landsat imagery, it is not possible to gain a high-level overall accuracy in forest stand-level variables. In conclusion, a relatively limited range of training data sets in our research seemed to be the cause of our classification errors in table 3.7.

The classification scheme also can be an issue to be considered here. The stand age 15, which works as a standard age to decide mature or premature forest areas, should be reconsidered as a correct number because trees can grow in different rates of speed and so some trees can be still premature after stand year 15. It means that until the age of a stand reaches about 20, the variation of biophysical structures such as biomass is large. Then, it notifies that around stand age 15 some trees are mature but some still premature. Thus, training data sets of mature forest areas and premature forest areas cannot be separated clearly so that reference data near the age 15 may indicate pixels can be misclassified by the *k*NN image processing classifier, and we can research further which age is more suitable for a standard age to decide premature or mature forest areas. In addition, we did not conduct various types of *k*NN methods with different values for weight matrix for euclidean distance to test a simple and standard method of each classifier. Presumably, testing diverse values for weight matrix for Euclidean distance can produce better accuracy results. However, generally the *k*NN method was regarded as one of the suitable methods for estimating premature forest areas among all the methods we tested in terms of overall accuracy, effectiveness in its uses and versatility.

In summary, overall accuracy and the kappa coefficients for each image processing classifier are presented in Table 3.8. Overall accuracy of MLC is 82% and the highest among all of them. The method of *k*NN followed with the overall accuracy 61% and the overall accuracy of regression analysis is 57%, which is the lowest among all of them. The kappa coefficient of MLC is 0.63 and that of *k*NN becomes 0.22. The kappa coefficient of regression analysis becomes 0.14.

Table 3.8: Overall accuracy and the kappa coefficients for each image processing classifier

Method	Overall accuracy (%)	The kappa coefficient
Maximum likelihood Classification	82	0.63
Regression analysis	57	0.14
k-Nearest Neighbors	61	0.22

Error (or confusion) matrix is used the most widely for accuracy assessment in land cover classification (Foody, 2002). Overall accuracy shows us relative effectiveness of each method and represents the accuracy of the entire product. In MLC, there are many correctly classified reference points in both premature stands and mature stands and that made the overall accuracy highest among them. The *k*NN method also shows relatively high value of overall accuracy. However, considering MLC the number of reference data that are correctly classified as other areas was relatively small in the *k*NN method. Thus, we can see that in MLC the possibility of other areas (except premature areas) being misclassified as premature forest stand is not so high, but in the *k*NN method it is relatively high. As for the results for regression analysis, the overall accuracy was relatively low, and we can see that we do not have enough correctly classified premature stands.

Basically the overall accuracy does not show the accuracy of individual categories (Story and Congalton, 1986). Producer's accuracy and user's accuracy indicate such accuracy of individual categories, and interpretation of each value is important. Producer's accuracy shows us how well a specific area can be mapped, and user's accuracy indicates how well the map represents what is really on the ground (Story and Congalton, 1986). In terms of producer's accuracy for premature forest areas, the *k*NN method showed the highest value, 74%, and MLC the second with the value 69%. Thus, *k*NN will map premature forest areas more correctly than other methods as a producer. Regarding user's accuracy for premature forest area, MLC was found to be the first in ranking among the three methods, followed by *k*NN. Thus, for users, a classified map using MLC among the three methods is more credible than the others.

Although the overall accuracy with producer's and user's accuracy provides valuable information, it can be criticized in its uses because in some cases all entities are classified into the correct category by chance (Foody, 2002; Congalton, 1991). Foody et al. (2002) noted it is likely that there is no a single standardized method of accuracy assessment and reporting. The kappa coefficient can compensate for this defect in that an estimate of kappa adds the off-diagonal elements in the error matrix indirectly when it is compared with the overall accuracy that only incorporates the major diagonal elements (Congalton, 1991). Therefore, the amount of errors in an error matrix decides the degree of agreement in the two different accuracy tests, which means that as the amount of errors decreases, the results of two different accuracy tests agree more with each other. The kappa coefficient of MLC 0.63 can be interpreted as a moderate agreement and that of *k*NN, 0.22, and that of regression analysis, 0.14, can be regarded as poor agreement. The accuracy rankings are consistent in both overall accuracy and the kappa coefficient. Although there are some errors in the matrix, it was not at a level that warranted changing the ranking of accuracy in the overall accuracy and the kappa coefficient method.

Young forest areas are characterized as lower heights and smaller stems than old forest areas. Also, it is likely that the amounts of chlorophyll in young forest areas are less than mature forests areas because young forest areas have a relatively smaller number of leaves, and the size of leaves are smaller than those of mature forest areas based on the condition that the number of trees is the same in stands of the same size. Therefore, LiDAR data will be beneficial to estimate young forest areas in that LiDAR data will provide height data in detail. In addition, as we infer based on the results of MLC, it is likely that soils between small trees are exposed to Landsat imagery more than mature forest areas. Thus, young forest areas probably can show spectral signatures including the mixtures of soil, stems, grass, and relatively less chlorophylls of young trees while mature forest areas show spectral signatures of relatively more chlorophyll of mature trees. Thus, it seems that satellite imagery having smaller spatial resolution will have an enhanced ability to capture such spectral signatures of mixtures of soil, stems, grass and the characteristics of young trees.

In addition, because in the edge of premature stand areas can be mixed with other areas like mature areas, a smaller pixel size can be beneficial in that small size pixels can minimize such error coming from the edges of premature forest areas. Similarly, mature forest areas having small isolated premature forest areas within 30 m × 30 m in size will cause some confusion with the spectral signature of other mixed areas using Landsat imagery. Thus, a forest stand in 30 m × 30 m in size which is classified as mature using Landsat imagery can be divided into some premature forest areas and some mature areas by any satellite imagery having smaller spatial resolution. However, the satellite imagery having smaller spatial resolutions than Landsat imagery can take probably more time and costs to cover the same extent of study areas. Therefore, the selection of suitable satellite imagery in terms of spatial resolution must be conducted carefully based on the extent of the study area, forest stand level characteristics, research time, and budget. In addition, because Landsat imagery only provides a horizontal perspective of the landscape, ancillary data describing a vertical image like LiDAR data will be more helpful (Kim et al., 2012). Especially in forest areas of mixed stands, ancillary data like broad-scale land classes, inventory plots, and LiDAR will be more beneficial in enhancing the results.

Boyed et al. (2003) asserted that each image classification has its limitation, and we need to select one of them according to the application and the environment. To have better accuracy, diverse image processing classifiers such as decision tree, neural network, and kriging can be considered to be tested especially in the estimation of age structure. We might have insight into which image processing classifiers might be more suitable for the estimation of forest age structures according to the geographic conditions and applications. Further studies in each method used in this research are essentially required to overcome the previously discussed limitations and can possibly offer a better way to enhance the efficiency or accuracy of each image processing classifier. Although the error matrix has been used the most widely and suitably for accuracy assessment, using the error matrix without any doubt can be problematic in that the basic assumptions for accuracy assessment sometimes are not satisfied (Foody, 2002). Congalton (1991) suggested various perspectives for further considerations such as ground data collection, spatial autocorrelation, sample size, and sampling scheme when performing an accuracy assessment. Such considerations are strongly suggested to increase assessment accuracy in land cover classification.

As the limitation in our research, we did not consider the stand density. In the case of low density of premature forest stand, it would not be easy to be represented as premature forest stand. Such premature stand in low density can be confused as the bare land or grass land in the interpretation of spectral bands of Landsat images. We think that some premature forest stands were misclassified because of this low stand density matter. In addition, according to stand density of premature stands, the signals of each band of Landsat images can be influential. Thus, stand density might be carefully considered as training data. We did not categorized tree species in this research. Labrecque et al. (2006) found out that the mixed stand class showed the largest RMSE values than the other species in the estimation of biomass. Lu et al. (2004) also found that tree species composition influenced vegetation reflectance. Therefore, even general classification of species will be beneficial to enhance the accuracy and compare strong and weak points of each method. In this research, we just used age structure as stand-level characteristics because basically we tried to estimate young forest area. However, it is suggested to test if other stand-level characteristics such as biomass or height can be more usefully employed to classify young forest area in combination with Landsat imagery. In this research we did not consider topography in our study areas although we can misunderstand the signals of Landsat imagery by distortion that came from topography (Zheng et al., 2007). After carefully dealing with the influence on Landsat imagery by topography, it is possible to minimize some errors and have better classification results.

Landsat imagery has been practical in the estimation of forest stand-level variables with the spectral bands and their combinations in terms of overall accuracy (Cohen et al., 1995; Steininger, 2000; Kim et al., 2012). Particularly, Southworth (2004) analyzed Landsat TM band 6 for land cover classification in the state of Yucaton, Mexico. They found that land cover classes are related strongly to band six calculated black body temperatures. Given such research, Landsat TM thermal band 6 is also included in our research and it is required to test further if only Landsat TM band 6 can be used effectively for the discrimination of young forest areas. Vegetation index such as NDVI or EVI seem to improve our results in that NDVI is sensitive to chlorophyll so can assess whether the observed image has live green vegetation or not, and EVI is designed as an optimized index for vegetation signal (Huete et al., 1997; Zheng et al., 2007).

Here, we intended to describe very standard methods in each classifier to compare the advantages and disadvantages in Landsat data applications for the use of Landsat imagery to estimate young forest areas rather than doing our best to enhance the accuracy results in each classifier. As further research, given classifiers which seem to be suitable based on the results of accuracy, we can investigate how the accuracy can be increased with any possible ways and data including diverse satellite combinations, various combinations of spectral bands in used satellite data, and diverse approaches in the uses of classifiers. In this research, although there is scope that can be enhanced, it is confirmed that Landsat imagery in combination with some spatial analysis image processing classifiers such as MLC can produce reasonable results of estimating young forest areas. However, still accuracy must be enhanced (especially in the small pixel scale research) and model transference between different geographic areas remains a challenge.

6. Conclusion

Tools for the use of FIA data were used to estimate the number of pre-merchantable trees in Georgia. Among the tools, the results from FIDO showed similar results compared to FIADB-Lite. FIDO is a web-based program for the use of FIA data and easily runs without the user having to understand the underlying data structures and can produce very correct and detailed forest stand results. By the results from FIDO, we come to know that the county of Clinch has the highest number of pre-merchantable trees and Webster county showed the highest percentage of pre-merchantable trees against all number of trees.

To estimate premature forest stands whose age is 15 or less, we used three image processing classifiers: MLC, regression analysis, and *k*NN. In terms of overall accuracy and the kappa coefficients, MLC produced the most accurate results for the estimation of premature forest stands and the *k*NN method ranked second, and the results of regression analysis were the least accurate. It is proven that Landsat imagery in combination with image processing classifier MLC provide reasonable and credible results for the estimation of premature forest stand area. In MLC, more representative training data for each class seems to be essential for better accuracy results, and in the *k*NN method, plot samples as training data covering the entire study area are strongly required to enhance accuracy results. Also, the *k*NN classification scheme must be reconsidered. Linear regression analysis did not produce reasonable accuracy results, thus different types of regression analysis such as logistic regression or non-linear regression analysis might be considered. Each of the classifiers used in this research can be researched more deeply in diverse ways to enhance accuracy results. For example, in MLC we can think about a different classification scheme for each class, and in regression analsysis, non-linear regression or logistic regression can be considered. For *k*NN, various k values can be tested to determine which value might be suitable using relevant methods. Other satellite data with especially smaller spatial resolution than Landsat imagery and various image processing classifiers that are increasingly used such as krigging and neural networks can be tested to increase the efficiency and accuracy results for estimation of forest age structure.

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CHAPTER 4

THE ANALYSIS OF PINE STUMPAGE PRICES BASED ON TIMBER SALE CHARACTERISTICS OF THE SOUTHERN UNITED STATES

1. Introduction

Forest landowners often need access to current timber market information. Since timber markets basically depend on the supply and demand, timber buyers and sellers need up-to-date timber market information. However, it is not an easy task to predict timber price (Mei et al., 2010). Timber market is a function of the relationship between timber and a variety of factors, such as wood consumption, wood supply, production technology, finished product demand, and stumpage prices, and also the change in timberland ownership may have had a significant influence on timber markets (TMS, 2009). Delivered prices include harvesting, transportation, and other markups above the stumpage price, and fuel costs and distances to mills will have effect on transportation costs, where wood quality and tract size are the main factors concerning harvest costs (TMS, 2009).

The hedonic price method is an approach which most commonly uses regression analysis to estimate the implicit values of characteristics from a value of commodity price (Rosen, 1974). In the process of manufacturing, some production inputs could be diverse and have significantly different characteristics. In such cases, a hedonic pricing approach is suitably employed for estimating the implicit prices of the various characteristics of an input and the demand for the input subsequently (Ladd and Martini, 1976). Thus, a hedonic model can be used to explain production factors or the prices of differentiated products. This hedonic price approach has been adapted to timber markets with heterogeneous inputs such as species composition, tree size, volume, and quality based on the assumption that such characteristics affect the lumber production (Puttock et al. 1990). We can efficiently analyze the implicit values of independent variables for stumpage price and can bring results about the derived demand of heterogeneous inputs for timber markets using hedonic price functions.

Timber Mart-South (TMS) publishes quarterly southern price reports. They started to report timber prices in 1976, and market news in 1996. In this paper, based on the TMS data (TMS, various years) and a variety of reports about timber markets in southeast United States, we have analyzed the stumpage detail characteristics and their influence on pine stumpage prices using a hedonic price function with the objective of providing better insight into the change of stumpage prices with related timber sale characteristics and anticipated demand for each input.

2. Literature review

2.1 Reports and analysis on southern stumpage price

The southern U.S. has more private ownership than the other major forest areas in the country. Newman (1987) stated that southern markets have long been major sources of softwood stumpage production in the United States. It was found that in 1976 almost half of total softwood timber removals in the country and half of the total additions to softwood inventories were produced in the southern area (U.S. Forest Service, 1982). Haynes and Adams (1985) projected that the southern region could comprise up to 51% in total removals and up to 61% in total growth by 2030 based on various assumptions regarding the stumpage market characteristics. In 2006, the southern area had 62% of the country's total growing-stock removals (Smith et al., 2009). Binkley and Vincent (1988) reported past tendencies and prospects for the future regarding timber prices in the U.S. South. They noted that southern pine stumpage prices had risen at a real rate 4.6% per year before World War II and since then the real rate of increase was decreased into 3.1% per year. They also projected the median estimate from 1990 to 2010 would be a real rate 1.9% per year. Given TMS data (TMS, 2009), we found that the stumpage price in the southeast U.S. increased rapidly from 1990 to about 1998, and since then it showed a tendency of decrease until 2008 with occasional fluctuations.

Adams and Haynes (1991) researched the future prospect of softwood timber market. They projected that nonindustrial ownerships cannot maintain previous growth rates in softwood harvest in the period from about 1991 to 2015. However, they asserted that if high planting rates during the 1980's are conducted in next century, it seemed that harvest could be increased afterwards. On the contrary, it is noted that industrial harvest will maintain increasing rates, but it is likely that it is not enough to offset the shortfalls by nonindustrial ownerships. Wagner et al. (1994) estimated economic effects of environmental regulations on southern softwood stumpage markets. They analyzed a range of southern softwood changes and found that timber producers in aggregate seem to make a positive effect initially in the short run. They also found that the environmental regulations produced a net gain for timber producers, while it made stumpage buyers a net loss. Sun and Kinnucan (2001) researched the economic impact of environmental regulations on southern softwood stumpage market. Contrary to the research by Wagner et al. (1994), they found that environmental regulations produced similar costs for timber producers and consumers.

2.2 Methods for the estimation of timber value

Newman (1987) presented an econometric analysis of the southern softwood stumpage market from 1950 to 1980. He used three stage least square regression techniques on both supply and demand system of pulpwood and solidwood (combined lumber and plywood) markets. The three stage least square regression techniques provided simultaneous parameter estimation of market systems. Haight and Holmes (1991) analyzed monthly and quarterly series of stumpage prices in terms of stationarity with a test to determine whether a time series variable is non-stationary using an autoregressive model for loblolly pine in the southeastern United States. The statistical results showed that a non-stationary random walk model can be more suitable for the quarterly series of average prices. Otherwise, they showed that stationary autoregressive models can be efficiently employed for monthly series and for the quarterly series of opening monthly prices which is made by sampling the monthly series in quarterly intervals. Wagner et al. (1994) used applied welfare analysis and current stumpage market conditions to compute the estimate of economic effects of environmental regulations on southern softwood stumpage markets. G Kinnucan (2001) presented an applied welfare analysis method which fixed a flawed procedure designed by Wagner et al. (1994) and is easy to apply. Hensyl (2005) examined influences of land and ownership characteristics on the price of stumpage in Virginia's nonindustrial forests.

Based on data of timber procurement personnel and sawmills from central Virginia a price equation base model and bid equation base model were developed. The effect of the decrease in both tract size and the amount of harvest and the behavior of landowners on marginal values of sale characteristics was analyzed. They also assessed how the fragmented forest affects the competitiveness regarding timber sale. Mei et al. (2010) modeled and forecasted the stumpage price of pine sawtimber with various time series models in the U.S. South. In 12 southern timber regions, they developed a univariate autoregressive integrated moving average model as a benchmark and applied other multivariate time series methods in comparison with a discrete-time framework. Under the continuous-time framework, they fitted both the geometric Brownaian motion and the Ornstein-Uhlenbeck process to the underlying data. They found that the vector autoregressive model produced more accurate results in the 1-year period by the mean absolute percentage error criterion. They also found that seven among 12 southern timber regions played crucial roles in the long-run equilibrium and market risks are well captured by conditional variances and covariances from the bivariate generalized autoregressive conditional heteroscedasticity model.

The hedonic pricing method has been used to estimate economic values for environmental services that directly have influence on market prices. The hedonic pricing method is based on the premise that the price of a marketed good is related to its characteristics, or the services it provides. Buongiorno and Young (1984) predicted the market value of sales in Chequamegon National Forest. They developed a multiple regression made with 14 independent variables and adapted stepwise regression with the independent variables which are relevant to the high bid on a competition of timber sale. They found that a simple linear model explained 93% of the variance in high bid for competitive sales using data from 1976 to 1980. Puttock et al. (1990) estimated stumpage prices in southwestern Ontario using a hedonic function approach. They expected that the stumpage price was influenced by various characteristics of timber used in the production of lumber. They estimated hedonic price functions for timber using pooled time-series cross-section data which are driven by a large sample of timber sales.

Munn and Palmquist (1997) estimated hedonic price equations using stochastic frontier estimation procedures for stumpage prices. They asserted that because the distributions of consultant and nonconsultant sales are not normal enough, ordinary least squares (OLS) is not adequate for estimating hedonic price equations for a timber stumpage market. Their new model and estimator are regarded as more suitable for timber markets than the traditional hedonic model and ordinary least squares (OLS) procedures with applied statistical techniques developed for stochastic frontier analysis to hedonic price functions. Their model will be more credible of such timber markets when there is uncertainty of price on both sides of buyers and sellers, and empirical results supported this model. Vasievich (1980) quantified the effect of timber sale factors on the costs of conducting timber sales and prices paid for the sales using a linear regression model. He used data from timber sale reports by Indiana State Forests and analyzed 11 site and sale conditions statistically. Leefers and Potter-Witter (2006) estimated hedonic price model to gain insights into timber sale characteristics and competition for public lands stumpage. They studied Lake States national forests and land managed by the Michigan Department of Natural Resources (MiDNR) to give useful information about the stumpage price impacts of sale and institutional sale characteristics. Based on empirical results, they found that the models within the same geographic region cannot be transferred easily to other regions. Sydor and

Mendell (2008) analyzed timber bid transactions using hedonic regression techniques in central Georgia. They estimated a regression model of softwood stumpage prices from pay-as-cut transactions against timber sale and stand characteristics.

2.3 Variables for timber appraisal methods

Buongiorno and Young (1984) found the relationship between timber sale areas and bid prices are correlated positively. Murray (1995) measured oligopsony power with shadow prices for pulpwood and sawlogs markets and found there is more oligopsonistic power in pulpwood market than the sawlog market. Puttock et al. (1990) noted that stumpage prices increased as the quality of timber improved and found hauling distance to the purchasing mill severely influence the stumpage price. Hubbard and Abt (1989) found that logging conditions affect stumpage price positively and significantly in Florida, while using logging conditions a dummy variable. Dunn and Dubois (2000) found that higher stumpage prices were driven by longer contracts between sellers and buyers. Leffler et al. (2003) found that as the percentage of pine sawtimber is greater, auctions occur more often on timber tracts. Thomas et al. (2004) examined a bid price equation for national forest timber sales in western Arkansas and southeastern Oklahoma. He found that the value of per unit volume of sawtimber become greater for larger sales because due to the economies of size buyers pay more per unit on large sales. Leefers and Potter-Witter (2006) used hedonic price model to provide insights about the significance of variables. For their final model of stumpage prices, they focused on species-product composition of sales, number of species and products, regional location, administratively set sale contract length, and sale timing, competition, and firm size. Sydor and Mendell (2008) found that timber size, timber quality, and stand site characteristics were crucial to the variability for cut pine sawtimber stumpage prices. They found that the period from 2002 to 2004 was characterized the lowest relative market risk. Kilgore et al. (2010) found that stumpage prices are increased by longer contracts in Minnesota State Forests. Therefore, the variables of larger sale size, wood quality, logging conditions, and longer contract lengths seem to influence stumpage prices positively.

Track size has effect on forest management. Hall and LeVeen (1978) examined the relationship between farm size and production costs in California. They noticed that the long-run average cost curve initially declines rapidly and then became flat as track size got larger. They found that relatively modest sized farms (100-320 acres) are in the stable cost area of curve. It was also found that as track size was reduced, average costs increased. They detected that the costs change in different ways according to the farm types. For example, they have found that the highly mechanized crops kept declining costs slowly, but the costs in vegetable and fruit crops did not show substantial decline after initial rapid drop. They concluded that not only the economies of size but also management, the overall institutional structure, and resource quality are so crucial factors as the sources of declining production costs. Olson et al. (1988) developed "equations for estimating stand establishment, release, and thinning costs in the Lake States". They investigated how costs per acre change as the size of project area increases. They found that in the relationship between cost per acre and size of project area, average manual planting costs leveled off and started to stabilize at about 18 acres, machine site preparation costs at about 40 acres, aerial spraying costs at about 50 acres, manual release costs at about 40 acres, and cost of manual thinning at about 50 acres. The cost of prescribed burning was minimized at about 64 acres. Vasievich (1980) found that in southern national forests the size of burn and age of rough strongly affected cost per acre. He discovered that the burning cost was $4.82 per acre for 50-acre burns in 12-year rough (years since last burn) and $0.35 per acre for a 2,400-acre burn in a 4-year rough. Gardner (1981) researched the effect of tract size on the cost of reforestation. He found that reforestation costs became lower for relatively large tract sizes of 50 acres and increased for smaller tracts sizes as less than 20 acres. The costs were prohibitive for tracts from 10 to 20 acres. It is noted that relatively small forest landowners have less money and labor available for reforestation, and thus it is inferred that that paucity of money and labor increased the cost for reforestation (Clawson, 1957; Bhahurothu, 2011). Guldin (1984) researched the influence of site characteristics and preparation practices on costs of hand-plating southern pine. He found that the hand-planting cost was the most expensive for planting contracts between 140 and 250 acres. Up to 140 acres, the hand-planting cost keeps increasing, and from 250 acres to 500 acres, the hand-planting cost decreased.

Tract size also affects timber harvesting costs. Cubbage (1983) simulated average harvesting costs on tracts from 5 to 360 acres, and found average costs increased in tracts below 50 acres. They noticed that large moving expenses made highly mechanized systems more sensitive to tract size changes, but costs of pre-hauler systems were not so much sensitive to tract size changes. He also determined that excessive harvest costs were paid for manual tree length systems and highly mechanized full-tree system on tracts less than 60 acres. Cubbage and Harris (1986) examined whether tract size was a factor limiting planting, harvesting, management and marketing aspects of timber management. Based on their observations, most costs were minimized at tract sizes from 40 to 50 acres. They observed that average costs initially decreased and at some point it started to stabilize as tract sizes became larger. Greene et al. (1997)

researched harvest cost implications of changes in the size of timber sales in Georgia. They evaluated three logging systems and made a spreadsheet in the Auburn Harvesting Analyzer. They noticed that in Georgia the size of individual forest stands and timber sales are slowly decreasing. They concluded that these trends will make the cost per acre increasing considering cultural practices for forest tracts and the cost for harvest. Baker et al. (2010) examined the impact of timber sale characteristics on harvesting costs. They collected timber sales data in the southeastern United States from 2000 to 2008 and examined the changes in harvest tract characteristics. They observed an increase in average tract acreage and substantial increase in partial harvesting. They found that logging costs increased in small tracts with low harvest volumes and these costs decreased if the sale characteristics values increased.

2.4 Stumpage detail reports

Stumpage Detail Reports from Timber Mart-South described delivered prices for pine sawtimber, which have been declining since 2005. They found fuel prices have climbed and remained at high levels, therefore stumpage prices have fallen and the amount of pine sawtimber available on the timber market was reduced. That made the market demands shifted to pine and hardwood pulpwood, hardwood sawtimber, and pine power poles during previous quarters before 1st quarter 2009. From 1994 to 2009, highway diesel fuel prices have doubled in the last 15 years. It seems to be that diesel prices mainly influence harvesting and transportation costs, thus the current rates of pine sawtimber were derived by the change of diesel fuel prices. Volatile fuel costs make managing logging and transportation operations more difficult. Because stumpage is residual of delivered prices, delivered and stumpage prices change in similar trends or tendencies. Thus, changes in harvest and transportation coast can change the amount of stumpage to landowners based on tract size, wood quality, fuel cost, and distance to the mills.

In detail, Stumpage Detail Reports present the change of delivered pine prices from 1976 4th quarter to first quarter 2009 (Figure 4.1). Pine sawtimber delivered prices started from about 15 US$/ton and had been maintained around $25 until 1990 4th quarter. Since then, they increased dramatically and peaked in 1998. After that, they went down and up at 50 US$/ton, and from 2005 they showed the tendency to decrease. Pine sawtimber, chip-n-saw, and pine pulpwood showed very similar tendency in the change of delivered pine prices. However, notably from 2005 the delivery prices of pine sawtimber and chip-n-saw decreased but pine pulpwood kept increasing. Highway diesel fuel prices from 1994 2nd quarter to 2008 2nd quarter can found in Figure 4.2. It started from 1 US$/gallon and generally showed an increasing tendency and peaked in the 2nd quarter 2008. Since then, it has started to show a tendency of decrease. Haul rate per ton is calculated by multiplying published minimum haul distances by the minimum haul rate, and it ranged from $4.29 to $5.70. Average harvest costs did not show big variance from 4th quarter 2005. This confirms that delivered and stumpage prices change very similarly (Figure 4.3). The delivered price and stumpage price of pine sawtimber peaked at 1998 and almost was maintained that level until 2005. Since then, it has declined.

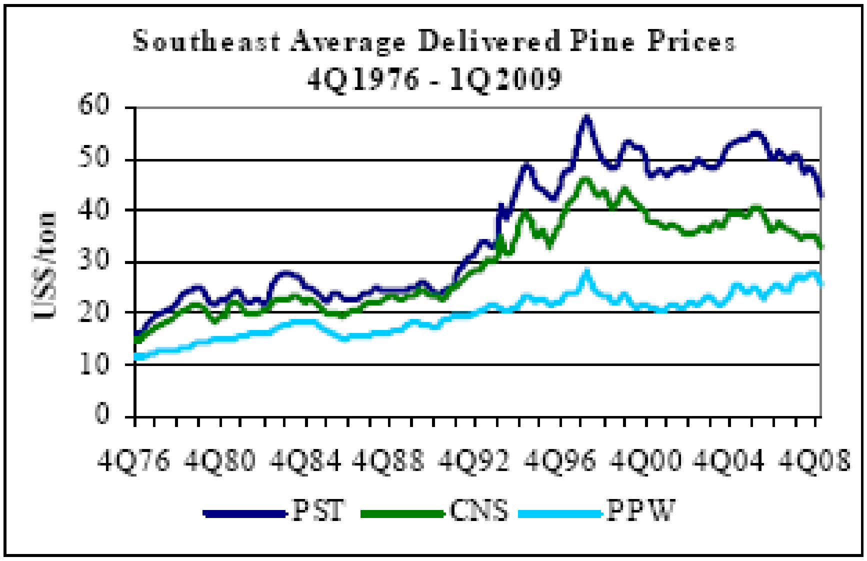

Figure 4.1: Southeast average delivered pine prices from 1976 to 2009, Pine Sawtimber (PST), Chip-N-Saw (CNS), Pine Pulpwood (PPW). (TMS, 2009).

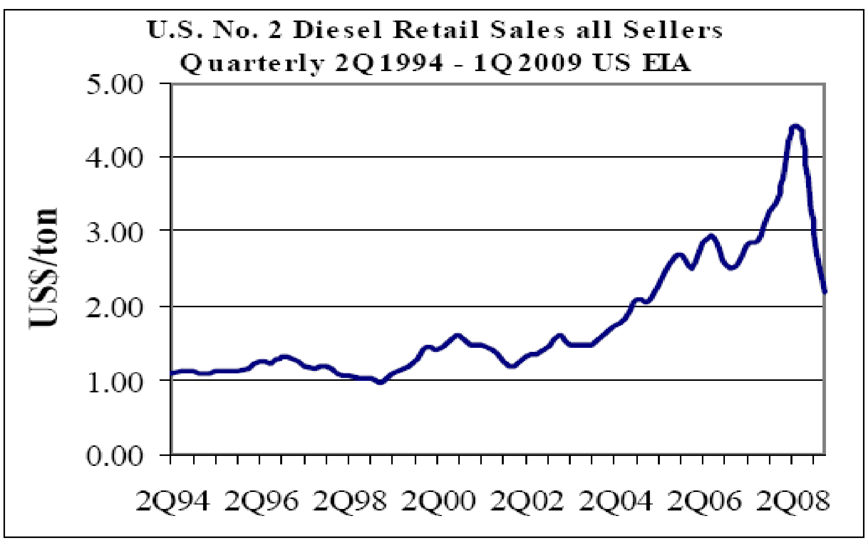

Figure 4.2: U.S. No. 2 diesel retail sales all sellers from 1994 to 2009. (TMS, 2009).

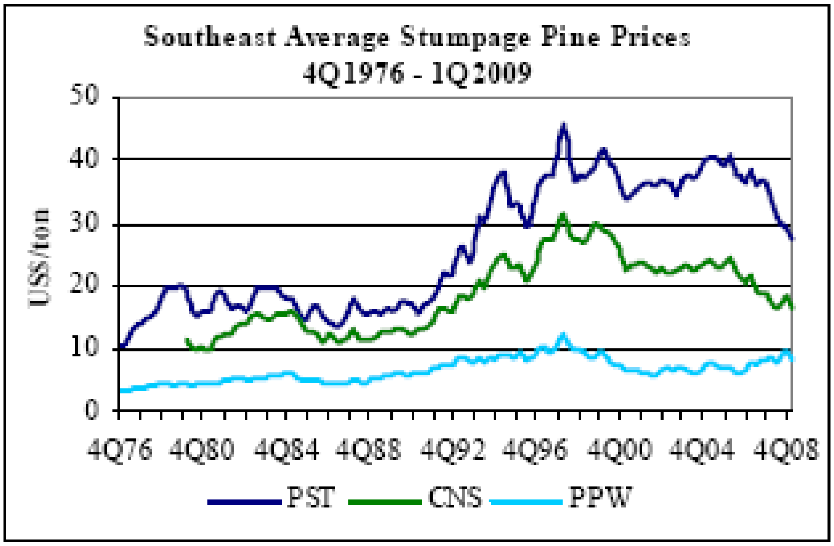

Figure 4.3: Southeast average stumpage pine prices from 1976 to 2009 (TMS, 2009).

After 2008, generally the South-wide stumpage prices kept decreasing, although in 2010 there was a little bit increase (Figure 4.4). However, chip-n-saw and pine pulpwood almost maintained the level of prices in 2008. We can find that several economic indicators which are related to stumpage price showed downward movements through Timber Mart- South Market News Quarterly (TMS, 2012). From 2008 up to now, housing remained depressed based on the US Census. In addition, US paper and paperboard production started to decline in 2008 and rapidly dropped in 2009. From 2009 to 2012, it has shown an increasing tendency. Diesel retail prices and crude oil prices have increased from 2007 to the second quarter of 2008. Since then, they have dramatically dropped beginning in the second quarter of 2008, and from the second quarter of 2009 they generally showed upward movements. Still it is likely that fuel prices affect pine sawtimber price changes and plus depressed housing and US paper and paperboard markets influenced the continuous tendency of decline in pine sawimber price.

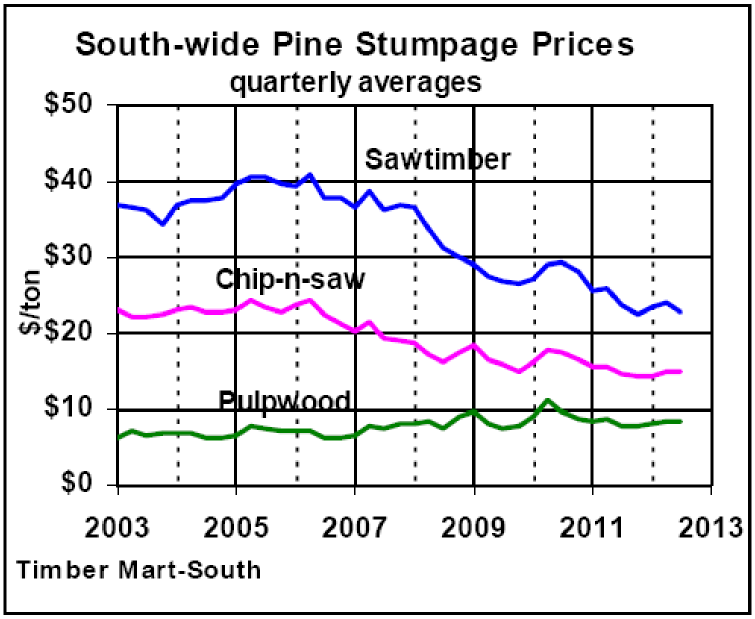

Figure 4.4: South-wide pine stumpage prices from 2003 to 2012 (TMS, 2012).

Based on TMS data, several reports have been produced. Yin and Caulfield (2002) examined the intra- and inter- market relationships using data from TMS. Two key parameters of growth rate and volatility of a price series were compared. They treated the mean value as the price growth rate and the standard deviation as a measure of volatility. They found that markets in the southeast vary widely across area, products, and species and also found that these markets have experienced two distinct development stages during 1977:1 to 1996:4. They found that deflation lowers the growth rate of a price series, but the effect on the volatility is small. It is shown that delivered prices for softwood had a slightly lower growth rates as opposed to that of stumpage prices, but the volatility of delivered wood prices series was much lower. They also found that delivered price of sawtimber traces stumpage prices vary closely; however, the same cannot be said for pulpwood. Through this research, they concluded that the assumption that price levels as well as their growth rates are the same across markets and over time is no longer proper and we cannot ignore the price volatility completely.

3. Data

We used quarterly stumpage prices reported from 1998 to 2007 in southern 11 states (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia) (TMS, various years). The data included area, county, sale date, sale type, sale size, total volume, total price, haul district, length contract, number of bids, high bids, low bids, type of cut, grade, market conditions, logging conditions, product type, and product amount (Table 4.1). The species and product group were classified into pine pulpwood, pine chip-n-saw, and pine sawtimber to be compared as references.

Table 4.1: Pine stumpage sales data

Name	Value	Unit
Quarter	1 - 4	
Year	1998 - 2007	
States	AL, AR, FL, GA, LA, MS, NC, SC, TN, TX, VA	
Area	1- 2	
County	Counties of each states	
Sale size	1 to 3,000	acres
Length contract	1 - 48	months
Number of bids	1- 22	
Type of cut	thinning, clearcut	
Grade	below average, average, above average, excellent	
Market conditions	poor, fair, good, excellent	
Logging conditions	poor, fair, good, excellent	
Stumpage/delivered	stumpage prices	$/tons
Product price	1~70	$/tons

3.1 Preliminary analysis on pine stumpage data

Stumpage prices (TMS, various years) were preliminarily analyzed to process raw data initially. The average of 10 years (1st quarter 1998 to 4th quarter 2007) of pine stumpage prices were compared to their average prices 4th quarter 2007 in Table 4.2.

Table 4.2: Average of 10 year and average of 4th quarter 2007 of pine stumpage price

	Pine pulpwood ($/tons)	Pine chip-n-saw ($/tons)	Pine sawtimber ($/tons)
Average of 10 year	27.19	27.19	43.29
Average of 4th quarter 2007	8.70	19.16	39.58

4. Methods

4.1 Hedonic price model using multiple regression model for estimating stumpage prices

We used the hedonic pricing method to estimate the stumpage price of pine sawtimber for economic values that affect the stumpage price. The hedonic pricing method is regarded as a preference method of estimating demand or value in economics. The fact that good prices in a market are influenced by their characteristics becomes a basis for hedonic price method. For hedonic price analysis, it is necessary to estimate how the dependent variable (stumpage price) is influenced by the independent variable (all various characteristics for stumpage price) and the hedonic price (implicit price), which is the change in stumpage price by the change in one of those characteristics, is estimated using the function of linear or non-linear (Boardman et al., 2011).

Based on the data analysis, a non-linear regression model was developed to estimate stumpage prices because the fitted line versus residuals was non-linear. Thus, we used a quadratic transformation. Pine sawtimber stumpage prices was estimated as:

$y_s = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_i x_i + \varepsilon$ for $i = 1,2, \ldots n$ Equation 1

where y_s = *stumpage price*, x_1 = *quarter2*, x_2 = *quarter3*, x_3 = *quarter4*, x_4 = *year* , x_5 = *sale type*, x_6 = *sale size*, x_7 = *sale size squared*, x_8= *length contract*, x_9 = *length contract squared*, x_{10} = *number of bid*, x_{11} = *harvest type* , x_{12} = *grade*, x_{13} = *market condition*, x_{14} = *logging condition.*

The regression variables used in multiple regression are described with unit of measurement in table 4.3.

Table 4.3: The description of dependent and independent variables.

Variable name	Unit of measurement and variable description
stumpage price	Pine stumpage price ($/ton)
quarter 2	Dummy variable, 1 if second quarter of the year, 0 otherwise
quarter 3	Dummy variable, 1 if third quarter of the year, 0 otherwise
quarter 4	Dummy variable, 1 if fourth quarter of the year, 0 otherwise
year	The year when the timber is harvested
sale type	Dummy variable, 1 if sealed bid, 0 negotiated
sale size	Total area harvested (ac)
sale size squared	Square of variable sale size
length contract	Contract period (month)
length contract squared	Square of variable length contract
number of bids	The number of bid during timber sale auction
harvest type	Dummy variable, 1 if clearcut, 0 otherwise
grade	Dummy variable, 1 if above average or excellent, 0 otherwise
market conditions	Dummy variable, 1 if above average or excellent, 0 otherwise
logging conditions	Dummy variable, 1 if above average or excellent, 0 otherwise

Quadratic forms were used for the variable *sale size* and *contract length* in our regression model. Quadratic forms are used to estimate parameters of threshold models, which have inflection point or threshold point. As the dependent variable changes in threshold model, quadratic terms help determine maximum and minimum values and help infer information related to economies of size. The inflection point is calculated as

Inflection point = $\beta_1 / -2\beta_2$ Equation 2

Where:

β_1 = linear term coefficient

β_2 = quadratic term coefficient

5. Results and discussion

The sale sizes of pine stumpage were presented according to each product group in Figure 4.5. The largest percentage of sale sizes was in the 1 to 50 acre range. The second largest group of sale sizes occurred with tract sizes ranging from 51 to 100 acres. In Figure 4.6, south-wide pine stumpage prices were presented by product group and sale sizes. In pine pulpwood, pine chip-n-saw, and pine sawtimber, the largest percentage of sale size was shown in tracts ranging from 151 to 200 acres in size.

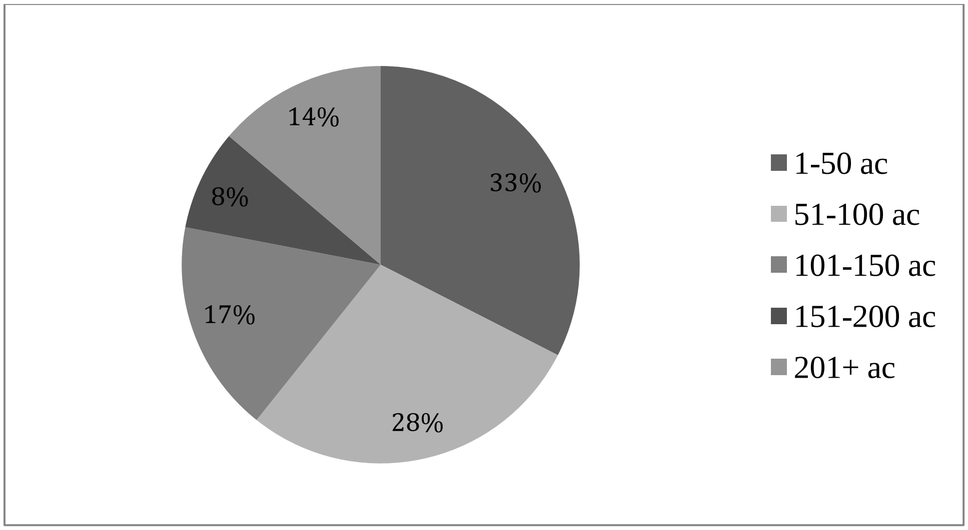

Figure 4.5: Sale size of stumpage pine sales, 1998 – 2007.

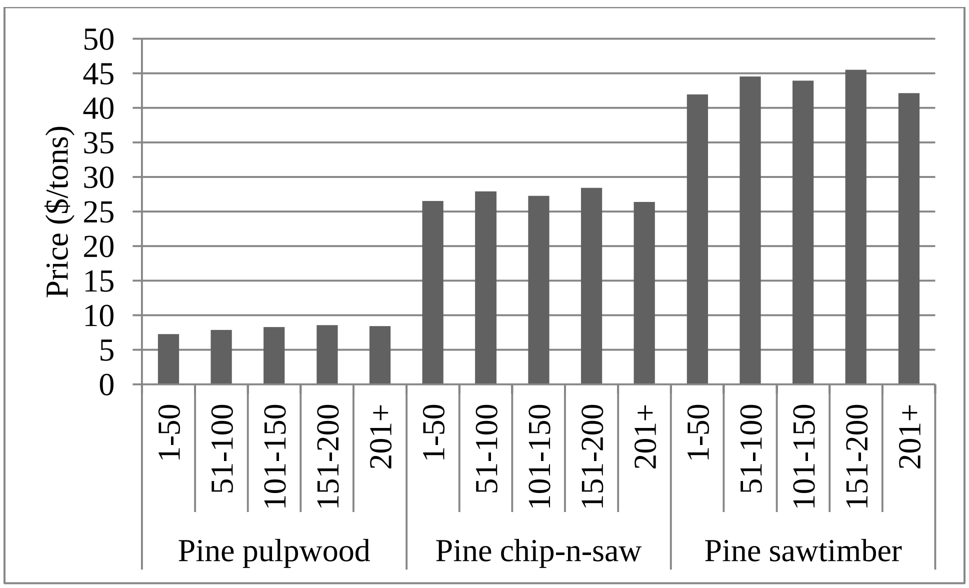

Figure 4.6: Average pine stumpage price ($/tons) by product group and sale size (acre), 1998 – 2007.

The percentage of harvest type was presented from 1998 to 2007 in Figure 4.7. Clearcuts formed 55 percent of the harvests and thinnings accounted for 45 percent. The average stumpage price was presented by harvest type and each product group in Figure 4.8. In pine pulpwood and pine sawtimber, the average price for thinning was higher but in pine chip-n-saw the price for clearcut was higher.

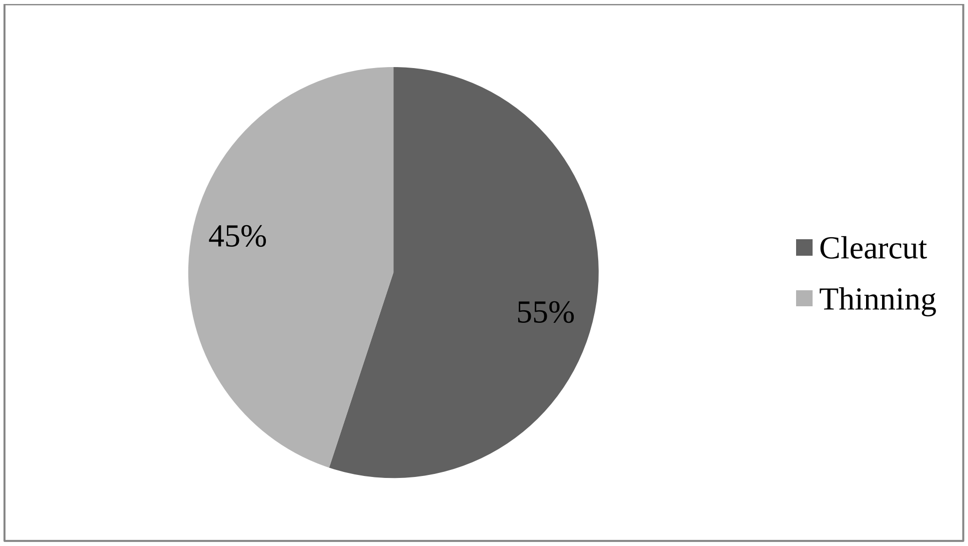

Figure 4.7: South-wide stumpage sales by harvest type, 1998 – 2007.

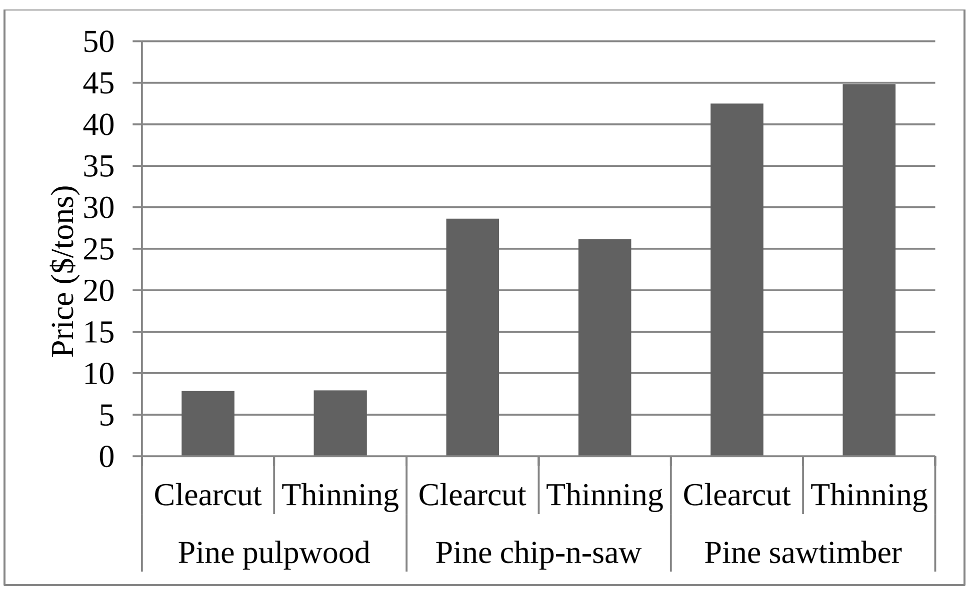

Figure 4.8: Average price of pine stumpage price ($/tons) by harvest type and product group, 1998 – 2007.

Based on stumpage sales, sale type information was presented in Figure 4.9. Negotiated sales accounted for 77 percent and sealed bid sales accounted for another 23 percent. Figure 4.10 describes the average price of pine stumpage price by sale type and product group.

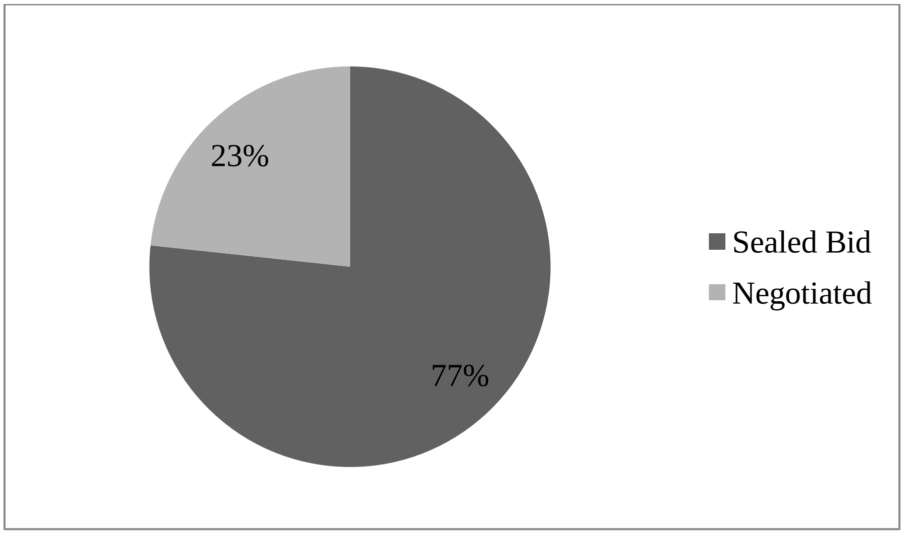

Figure 4.9: Southern stumpage sales by sale type, 1998 – 2007.

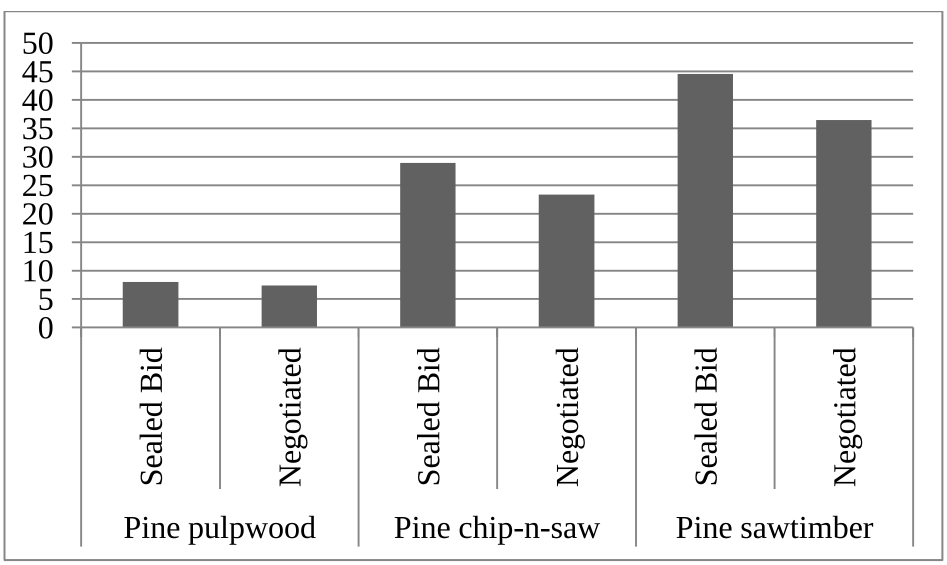

Figure 4.10: Pine average stumpage price by sale type and product group, 1998 – 2007.

For the regression analysis, we found missing data in 497 samples of sales. Thus the final sample size was 2,465 sales. We developed basic descriptive statistics for dependent and independent variables. We reported mean, standard deviation, minimum, maximum, and sum for variables (Table 4.4) and also reported the percentage of type 1 in each dummy variable (Table 4.5).

Table 4.4: Descriptive Statistics of variables

	Mean	Standard Deviation	Minimum	Maximum	Sum
stumpage price	44	12	0	70	109,980
sale size	104	122	2	3,000	258,463
sale size squared	25,658	193,470	4	9,000,000	63,606,273
contract length	17	7	1	48	42,702
contract length squared	341	232	1	2,304	846,441
number of bids	5	3	0	22	12,901

Table 4.5: The percentage of type 1 in dummy variables

Variable name	% of type 1
sale type	94.96
harvest type	56.03
grade	38.44
market conditions	17.06
logging conditions	21.94

Multiple regression analysis was conducted in R statistical software. The regression results are presented in Table 4.6. The model R-squared equals 0.1807 and adjusted R-squared 0.1767, which indicates that the goodness of fit of the model is relatively low. However, the model is globally significant based on the F-statistic. The likely reason for relatively low R-squared can in part be explained by the fact that we removed 497 observations of sales from the analysis. In addition, during the research period one notable thing is that southeast average pine sawtimber stumpage prices peaked in 1998 and have substantially dropped since then, which means there were some factors that influence on pine stumpage price severely that were not accounted for in this analysis. Particularly, based on the reports regarding stumpage prices (TMS, various years), the fuel prices increased from 1998 to 2007 and they seem to affect stumpage price. Puttock et al. (1990) found that the hauling distance greatly affects the timber price. It is suggested that such variables regarding the fuel prices and hauling distances need to be incorporated to acquire better fitted regression results. Although the pine stumpage price showed mainly a decreasing tendency, there were some main fluctuations in stumpage price change during the research period. It is likely that such a situation have also contributed to relatively low R-squared values, compared to other similar research using hedonic price function (Buongiorno and Young, 1984; Puttock et al., 1990; Leefers and Potter-Witter, 2006; Sydor and Mendell, 2008). Variables describing *year, contract length, number of bids, harvest type, grade, market conditions*, and *logging conditions* are statistically significant based on corresponding probabilities. Variables such as *quarter 4, sale type,* and *sale size squared* are significant at $\alpha = 0.01$. Further, *quarter 3* and *contract length* are significant at $\alpha = 0.0001$. Other independent variables except *quarter 2* are significant at $\alpha <$ 0.0001. Only variable q*uarter 2* is not significant even at $\alpha = 0.1$.

Table 4.6: Parameter estimates for pine sawtimber stumpage price regression model

Variable	Parameter Estimate	Standard Error	t-value	Pr(>|t|)
Intercept	39.73	1.495	26.582	0.000 ***
quarter2	0.7902	0.559	1.414	0.158
quarter3	-1.919	0.6085	-3.153	0.002 **
quarter4	-1.352	0.6088	-2.221	0.026 *
year	-0.6266	0.07954	-7.878	0.000 ***
sale type	2.091	1.02	2.051	0.040 *
sale size	0.008978	0.002664	3.37	0.001 ***
sale size squared	-0.00000367	0.000001626	-2.257	0.024 *
contract length	0.4019	0.1287	3.123	0.002 **
contract length squared	-0.02003	0.003692	-5.425	0.000 ***
number of bids	0.8403	0.08424	9.975	0.000 ***
harvest type	-3.306	0.4587	-7.207	0.000 ***
grade	2.606	0.4483	5.813	0.000 ***
market conditions	3.934	0.6167	6.38	0.000 ***
logging conditions	2.133	0.5488	3.886	0.000 ***

Note: Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

To investigate seasonal effects, quarters when sales occurred were represented by dummy variables with the *quarter 1*as the reference. Pine sawtimber prices in *quarter 3* decreased by $1.92/ton and in *quarter 4* decreased by $1.21/ton based on the *quarter 1* as the reference variable holding all independent variables constant. Although *quarter 2* is not statistically significant, it has a high coefficient value, indicating positive influence on timber prices. *Quarter 3* has the largest negative coefficient value among all quarters. Fiery (2012) illustrated the annual change of pine sawtimber with more detail information of monthly stumpage price trends in South-wide states. Based on the results of stumpage price changes in two different time scales, we can see that while mainly the yearly stumpage price maintained a decreasing tendency from 2010, the monthly changes of stumpage price relatively showed little bit more increasing tendency in quarter 1 and 2 than quarter 3 and 4. From their illustration, it looks like that although the quarter factors as dummy variables cannot change the main stream of stumpage price severely, it induces the minor and temporary changes in timber price. Such a similar tendency seems to be shown in our results for stumpage price change during our research period. The continuous variable *year* represents the year in which timber was harvested. This variable has a negative impact on stumpage prices which declined during the period 1998 to 2007. Pine sawtimber stumpage prices declined by $0.627/ton per year. Most of all, the increase of fuel price is considered a major reason for the decreasing tendency of stumpage price as we shown in literature review during the research period.

Basically as the *sale size* increases by one acre, pine sawtimber stumpage price increases by $0.009/ton initially. This result is in agreement with other research regarding sale size (Buongiorno and Young, 1984). Based on an interpretation of inflection point of sale size, as the *sale size* increases after reaching the maximum, the stumpage price starts to decline by $0.000004/ton with all other independent variables held constant, which means it is not whole lot. If logging and hauling costs tend to decrease as tract size increases, stumpage price seems to increase. The reason for such increase of stumpage price is inferred from the fact that delivered price equals stumpage price adds logging and hauling costs and based on assumption the delivered price should be maintained under other conditions are same, we saved the money in logging and hauling costs and can get higher price for stumpage. However, it seems that logging and hauling costs start to increase after reaching some point due to diseconomy of size.

Based on equation 2, we determined stumpage prices were maximized when sale sizes reach about 1,223 acres. This does not agree with our preliminary data analysis, which indicated that timber prices were maximized when sale sizes ranged from 151 to 200 ac, although the calculated inflection point (1,223) is within the range of input data. Basically the sale size results of preliminary data analysis are calculated based on all other independent variable are not constant. However, the results of inflection point for the sale size are calculated based on the assumption that all the other independent variables are constant. We guess that such difference seems to make a gap between preliminary results and a calculated inflection point. We infer that in real world there were some beneficial factors that influence high stumpage price in the sale size range from 151 to 200 ac, but theoretically diseconomy of size seems to work at larger sale size than that based on our data. In addition, although the preliminary results show the different maximum ranges to our calculated maximum point, the stumpage prices of all ranges in preliminary results are very close to each other. As same phenomenon, the coefficients for *sale size* and *sale size squared* reach almost zero, which means the slopes for *sale size* and *sale size squared* were extremely small and stumpage prices are very similar within all ranges of stumpage price, given our data sets of TMS during our research period (TMS, various years). We also infer that although during the research period the stumpage price had been decreased globally, it was almost maintained at a relatively high level, which means demands for stumpage consistent and enough not to work diseconomy of size. We need to further investigate whether a quadratic model is suitable for estimating a reasonable inflection point in timber markets, and which ranges of inflection values are calculated with data of different regions or time periods.

The *contract length* has similar impacts on prices as the *sale size* variable. As contract length measured in months increased so did pine stumpage prices by $0.402/ton. This positive relationship between contract length and pine stumpage price is also supported by other research (Dunn and Dubois, 2000; Kilgore et al., 2010). After reaching the maximum point, pine stumpage price decreased by $0.023/ton. The optimum contract length was calculated as 10 months based on equation 2 to get the highest stumpage price. Basically, it seems that as contract length increases loggers will have a more flexible time to harvest based on the market conditions, making positive impact on timber price, while as contract lengths last too long loggers cannot respond to properly the possible dynamic changes of stumpage market. However, the optimum of stumpage prices at 10 months can be a spurious interpolation due to insufficient data, because timber stumpage contracts typically run for 6 month periods and have options to extend and timber growth would be an important appraisal issue for longer term contracts. We have not captured that information in other models.

Sale type can be classified as a sealed bid sale or a negotiated sale. In our results, sealed bid prices tended to exceed negotiated sale prices by $2.09 per ton. It seems that sealed bid sales were associated with higher prices because it can provide opportunities to take more bids, thus enhance possibility to obtain higher prices. *Number of bids* also influenced pine sawtimber stumpage prices. As the number of bids increased the pine sawtimber prices increased by $0.84/ton per each additional bid. It is inferred that more bids provide more chance to get higher price. We conclude that pine sawtimber stumpage prices get higher in the case of sealed bid auctions and larger number of bidders. Clearcut as a *harvest type* had a negative impact on pine sawtimber price which is decreased by $3.31/ton than thinning, and the results is in agreement with the preliminary analysis in Figure 4.7. In general, we can expect that stumpage prices will be lower on thinning because the logging costs are higher. Logging costs for thinning tend to be higher since less volume per acre and per tract is being harvested and the trees removed are generally the smaller diameter stems in the stand. However, in our preliminary analysis the result is reverse in pine sawtimber stumpage price, and showed a positive coefficient on thinning. We infer the unexpected result came from the fact that usually the harvest on thinning is more focused on pine pulpwood and pine chip-n-saw than pine sawtimber because harvested timbers by thinning more tend to be more used for pulpwood and pine chip-n-saw. Thus, the stumpage price for pine sawtimber can be not a major issue for in the harvest by thinning, making the unexpected results happen specially during our research period. Another idea for the unexpected result can be that based on the assumption the demand for pine sawtimber is constant, the supply amount by thinning can be more limited than that by clear cut.

As expected, the presence of high quality timber (*grade* variable) had positive impact on stumpage prices. Above average or excellent grade had a positive coefficient 2.61, which indicates that above average or excellent quality increased prices by $2.61/ton. The g*rade* variable was statistically significant and the impact was relatively large. This result is in agreement with other approach about stumpage price for timber using hedonic function (Puttock et al., 1990). In a similar manner, the *market conditions* variable was statistically significant and positively related to stumpage prices with the highest coefficient value 3.934. This means that the presence of above average or excellent market conditions have larger impacts than the other sale characteristics on pine sawtimber timber prices. The better market conditions imply that the demand for timber is bigger by consumption more (Bhahurothu, 2011). Such increased demand for timber seems to make stumpage prices higher. The variable *logging conditions* is statistically significant and has a large value. When above average or excellent logging condition are present, the prices increased by $2.13/ton. This result corresponds with the analysis by Hubbard and Abt (1989). Although grade, market conditions and logging conditions as dummy variable showed big impacts on stumpage price, it is not easy to define a clear line between excellent or above average and average because the standards can be different according to real market, ground conditions, and one's perspectives. Thus, it is suggested that the coefficients are interpreted as values which are not absolute but implicit.

6. Conclusion

We developed a hedonic model for pine sawtimber based on various sale characteristics in non-industrial forest lands of 11 southern states in U.S from 1998 to 2007. A sample size of 2,465 was used and the model was globally significant. In this study it is evident that as sale size increases the price of sawtimber basically increases as well. When sale sizes are small buyers tend to pay less for timber because of higher harvesting costs. It was found that when sale size reaches 1223.4 acres the stumpage price was maximized through quadratic transformation. As contract length increased the pine sawtimber price basically increased, and when the contract length between the buyer and seller reaches 10 months, stumpage prices were maximized using quadratic transformation also. In quarter 2 of the year, sellers received higher prices than the other quarters. Sealed bid sales were characterized by higher stumpage prices as were the number of bids. Selective cuts showed a positive impact on timber price. The presence of excellent or above average level in grade, market conditions, and logging conditions made significant positive impacts on the price of pine sawtimber stumpage. This study will be useful mainly for owners of private forests to promote timber sales and to make more suitable plans for timber management in southern United States.

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CHAPTER 5

CONCLUSION

Landsat satellite imagery has been employed considerably to estimate forest stand-level characteristics over the last twenty years. In the estimation of stand-level forest characteristics using Landsat imagery we described the trends which have been popular in the recent 20 years and challenges which have been encountered. We noted that in general, research regarding the estimation of stand-level forest characteristics using Landsat imagery have increased during the research period although there were several partial decreases. We focused on the stand-level forest characteristics which are estimated using Landsat imagery, and the algorithms employed in the image classification processes. Given analysis on the results concerning the forest stand-level characteristics, we found that average forest height, crown closure, and stand age were less frequently addressed than the others, while the estimation of biomass was conducted more often. Although we tried to find which stand-level characteristic(s) is more suitable for estimation using Landsat imagery, and although one may find a characteristic to be the same or similar in a particular geographic area, we cannot conclude this for all areas because geographic traits, employed techniques, and ancillary data used differ depending on various research. The synthetic data derived from Landsat imagery allows us to clearly enhance the accuracy of results for various forest stand variables including age structure and biomass. However, biomass is a more dependable variable for the estimation of stand-level characteristics in some cases where very similar spectral signatures are shown, such as within young and old tropical forest areas forests. Ancillary information such as inventory plots or LiDAR data seems to be useful in increasing the accuracy results especially with forest stands that have more complex structures. With regard to the image classification techniques, we found that various types of regression analysis and *k*-nearest neighbor (*k*NN) imputation techniques were employed most widely. Other techniques such as neural networks, regression kriging, and maximum likelihood classification are increasingly being applied, but further research needs to be followed. Because in most cases the estimation of forest stand-level characteristics was poor at small scales and relatively good at larger scales (40-100 ha), large scale results should be carefully adapted to small-scale results. Although accuracy results show us that they are credible in multiple research areas with various combinations of ancillary information, it is not easily transferable to other geographic areas due to different types of vegetation, topographic, and climatic conditions. For the estimation of forest stand-level characteristics, the Landsat satellite imagery has been proven practical based on accuracy results of various research and might be continued as one of most important medium-resolution remotely sensing programs.

To provide valuable information about the quantitative knowledge on forest areas and to check the efficiency, availability, and pros and cons for each method, we investigated tools for the use of FIA data. For doing that, we calculated the quantitative information of pre-merchantable trees in the state of Georgia using FIADB-Lite and FIDO and compared the results. The results from FIDO and FIADB-Lite showed very similar results in the estimation of pre-merchantable forest areas at county-level areas. If one does not have good expertise about data structures in FIADB-Lite, FIDO is suggested to be used because it is web-based program and runs relatively easily.

As a practical effort for the estimation of forest stand-level characteristics, we estimated premature forest areas whose age is 15 or less using Landsat satellite imagery with three technologies: maximum likelihood classification (MLC), regression analysis, and *k*NN. Based on the analysis of the accuracy results, we found that MLC showed the highest accuracy results with an overall accuracy of 72 % and the kappa coefficient 0.44. The *k*NN method followed MLC with an overall accuracy of 61% and the kappa coefficient 0.249. The results of regression analysis were not satisfactory in terms of its accuracy values given an overall accuracy of 45.1% and the kappa coefficient -1.105. It seems to be that for MLC to operate efficiently in the estimation of forest stand-level characteristics, a training data set which covers each class distinctively is strongly required. MLC seems to be one of the efficient methods in the estimation of forest age structure according to our accuracy results. We confirmed that the *k*NN method needs a sufficient number of plots for training data to produce reasonable results, and then consequently it will enhance the accuracy results. It is likely that linear regression analysis is not so suitable especially for estimating the young age structure of stand-level forest areas because the relationship between stand age and spectral responses appears to not be consistently linear especially in young ages of forest areas. Diverse forms of regression analysis such as logistic regression or non-linear regression can be considered to be tested for further research assuming they are more proper for the estimation of young forest areas. Although there is room for further research, we confirmed that Landsat imagery can be employed efficiently in combination with some related technologies such as MLC and kNN for the estimation of young forest areas.

Given the information about stand-level forest conditions which are estimated using diverse satellite imagery, technologies, and field inventories, various types of models can be considered for estimating the change of forest stand-level variables, the stage of stand developments, or related timber prices. In particular, stumpage price changes have become a crucial issue for both timber buyer and seller. We have developed a hedonic model for the change of pine sawtimber stumpage price with diverse sale characteristics based on Timber Mart-South data of 11 southern states in United States reported from 1998 to 2007. It was shown that the model is globally statistically significant although the used sample size (2,465) is relatively small due to missing observations (497). To investigate seasonal effects, quarters when sales occurred were included as dummy variables. We found that *quarter 1* and *quarter 2* showed more positive impacts on stumpage price than *quarter 3* and *quarter 4*. Based on quadratic forms in variable *sale size* and *contract length* in our regression model, inflection points were estimated. As the *sale size* increased pine sawtimber stumpage price generally increased and *sale size* was maximized at 1,123 acres through the quadratic transformation. We also found that there is a positive relationship between contract duration and pine stumpage price, and the optimum contract length was calculated as 10 months using quadratic transformation. Sealed bid sale showed a positive impact on timber price and selective cut is characterized by higher stumpage price. Most of all, the presence of excellent or above average level in grade, market condition, and logging condition made huge positive impacts in pine sawtimber stumpage price. These results provide insight into the implicit meaning of sale characteristics, helping timber manager to develop a proper plan for timber management and to promote timber sales especially in southern United States.

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APPENDIX

Number of trees of pre-merchantable trees in selected counties of Georgia

County	Number of PMT byTree Diameter Classifications 1.0-2.9 in (1)	3.0-4.9 in (2)	Total Number of PMT	Total Number of all tree	% of Number of PMT against number of all trees
Appling (1)	78,732,473	26,117,418	104,849,891	146,604,980	72
Atkinson (3)	43,200,057	17,100,519	60,300,576	83,909,689	72
Bacon (5)	33,398,882	21,641,749	55,040,631	81,697,884	67
Baker (7)	15,679,426	3,635,676	19,315,102	29,952,026	64
Baldwin (9)	50,791,173	14,250,238	65,041,411	85,056,270	76
Banks (11)	31,912,950	6,553,470	38,466,420	49,175,406	78
Barrow (13)	15,225,175	2,800,585	18,025,760	23,707,777	76
Bartow (15)	117,773,648	34,819,616	152,593,264	183,639,942	83
Ben Hill (17)	27,889,056	18,961,622	46,850,678	71,082,944	66
Berrien (19)	107,612,574	26,493,379	134,105,953	164,572,981	81
Bibb (21)	33,060,691	7,123,056	40,183,747	50,353,789	80
Bleckley (23)	33,844,304	9,429,931	43,274,235	56,535,354	77
Brantley (25)	71,189,993	40,949,309	112,139,302	155,569,615	72
Brooks (27)	61,868,356	20,319,928	82,188,284	108,338,811	76
Bryan (29)	55,456,610	23,460,625	78,917,235	115,227,090	68
Bulloch (31)	124,304,467	32,833,902	157,138,369	210,882,587	75
Burke (33)	100,791,969	38,727,959	139,519,928	205,021,483	68
Butts (35)	41,203,326	11,293,539	52,496,865	63,429,150	83
Calhoun (37)	29,089,836	8,543,399	37,633,235	46,863,054	80
Camden (39)	106,823,729	36,531,255	143,354,984	198,989,944	72
Candler (43)	44,115,456	13,022,949	57,138,405	68,731,972	83
Carroll (45)	105,561,914	25,696,535	131,258,449	168,888,214	78
Catoosa (47)	6,782,504	1,356,501	8,139,005	12,044,435	68
Charlton (49)	100,038,850	47,233,166	147,272,016	203,098,614	73
Chatham (51)	29,363,032	14,003,908	43,366,940	60,795,379	71
Chattahoochee	35,128,795	13,339,001	48,467,796	65,930,475	74

(53)					
Chattooga (55)	100,368,072	25,361,864	125,729,936	155,631,482	81
Cherokee (57)	56,054,572	15,245,255	71,299,827	95,921,542	74
Clarke (59)	15,953,383	3,437,075	19,390,458	23,733,252	82
Clay (61)	32,017,010	9,429,931	41,446,941	52,663,627	79
Clayton (63)	7,360,696	1,288,903	8,649,599	10,767,201	80
Clinch (65)	160,427,737	85,908,689	246,336,426	342,452,999	72
Cobb (67)	9,510,588	2,503,151	12,013,739	16,020,994	75
Coffee (69)	90,668,408	30,230,750	120,899,158	158,099,360	76
Colquitt (71)	35,529,284	8,456,592	43,985,876	63,124,954	70
Columbia (73)	33,192,417	11,128,882	44,321,299	59,581,725	74
Cook (75)	42,313,788	13,321,976	55,635,764	69,479,687	80
Coweta (77)	103,411,519	24,475,326	127,886,845	159,454,075	80
Crawford (79)	80,823,150	24,962,475	105,785,625	127,255,652	83
Crisp (81)	39,009,441	9,169,271	48,178,712	58,222,305	83
Dade (83)	14,785,213	3,690,112	18,475,325	30,055,939	61
Dawson (85)	35,127,992	12,863,253	47,991,245	63,386,028	76
Decatur (87)	52,724,754	14,932,361	67,657,115	88,972,353	76
Dekalb (89)	13,887,461	3,235,088	17,122,549	24,162,577	71
Dodge (91)	94,626,778	28,382,073	123,008,851	161,154,705	76
Dooly (93)	22,569,052	9,255,911	31,824,963	44,012,607	72
Dougherty (95)	34,718,484	6,220,070	40,938,554	55,797,701	73
Douglas (97)	9,635,241	5,664,447	15,299,688	26,559,886	58
Early (99)	35,322,016	11,438,225	46,760,241	68,728,978	68
Echols (101)	116,797,747	46,778,209	163,575,956	202,783,151	81
Effingham (103)	87,512,196	35,158,158	122,670,354	169,783,991	72
Elbert (105)	68,645,504	17,842,656	86,488,160	110,086,184	79
Emanuel (107)	139,860,274	34,266,600	174,126,874	230,907,947	75
Evans (109)	31,460,805	6,716,484	38,177,289	51,439,985	74
Fannin (111)	71,685,470	23,060,514	94,745,984	124,773,413	76
Fayette (113)	12,775,983	3,096,379	15,872,362	23,158,559	69
Floyd (115)	79,150,415	30,248,416	109,398,831	139,846,872	78
Forsyth (117)	16,181,031	4,410,167	20,591,198	27,455,889	75
Franklin (119)	16,456,486	15,445,991	31,902,477	42,629,417	75
Fulton (121)	48,827,446	9,297,142	58,124,588	77,785,108	75
Gilmer (123)	79,568,013	26,590,324	106,158,337	150,945,324	70
Glascock (125)	40,703,909	10,619,753	51,323,662	60,949,426	84
Glynn (127)	53,257,516	19,846,714	73,104,230	95,680,328	76
Gordon (129)	50,040,358	13,564,814	63,605,172	78,079,852	81
Grady (131)	28,033,803	11,063,264	39,097,067	60,725,932	64
Greene (133)	103,789,659	41,788,030	145,577,689	182,788,683	80
Gwinnett (135)	41,512,252	9,612,953	51,125,205	66,322,916	77
Habersham	28,743,217	10,581,089	39,324,306	57,855,081	68

(137)					
Hall (139)	39,449,251	12,086,674	51,535,925	65,384,486	79
Hancock (141)	142,428,246	41,171,113	183,599,359	229,277,226	80
Haralson (143)	41,191,929	11,015,680	52,207,609	72,797,007	72
Harris (145)	99,495,701	41,901,239	141,396,940	185,120,652	76
Hart (147)	17,408,153	6,128,705	23,536,858	33,373,443	71
Heard (149)	60,552,657	21,492,771	82,045,428	103,829,695	79
Henry (151)	37,649,045	11,227,081	48,876,126	64,483,583	76
Houston (153)	23,824,990	11,945,426	35,770,416	53,914,384	66
Irwin (155)	41,999,883	9,776,132	51,776,015	65,784,736	79
Jackson (157)	54,791,210	18,531,189	73,322,399	90,394,670	81
Jasper (159)	98,331,302	30,415,533	128,746,835	164,600,905	78
Jeff Davis (161)	58,157,110	22,557,147	80,714,257	111,689,082	72
Jefferson (163)	71,783,516	33,008,501	104,792,017	144,384,943	73
Jenkins (165)	61,697,514	12,583,130	74,280,644	92,660,955	80
Johnson (167)	46,825,889	9,468,638	56,294,527	79,376,895	71
Jones (169)	126,244,988	33,573,922	159,818,910	187,370,053	85
Lamar (171)	64,272,189	11,126,820	75,399,009	87,283,094	86
Lanier (173)	38,433,749	16,827,458	55,261,207	68,064,791	81
Laurens (175)	155,595,789	45,749,569	201,345,358	260,731,212	77
Lee (177)	27,087,496	7,312,625	34,400,121	49,475,302	70
Liberty (179)	76,117,400	18,045,718	94,163,118	129,062,960	73
Lincoln (181)	57,231,473	9,871,135	67,102,608	83,234,613	81
Long (183)	114,497,332	28,881,493	143,378,825	180,897,274	79
Lowndes (185)	97,966,277	22,191,746	120,158,023	144,633,570	83
Lumpkin (187)	41,147,191	15,373,676	56,520,867	80,950,064	70
McDuffie (189)	40,421,199	18,363,085	58,784,284	77,768,041	76
McIntosh (191)	73,080,390	16,238,762	89,319,152	118,601,562	75
Macon (193)	78,335,129	14,580,295	92,915,424	111,365,151	83
Madison (195)	34,252,443	14,184,117	48,436,560	62,007,759	78
Marion (197)	52,979,970	21,447,384	74,427,354	100,388,214	74
Meriwether (199)	118,715,823	34,022,618	152,738,441	192,724,560	79
Miller (201)	27,964,119	6,242,312	34,206,431	44,446,464	77
Mitchell (205)	29,058,955	15,103,646	44,162,601	64,350,309	69
Monroe (207)	88,377,851	17,414,815	105,792,666	137,982,064	77
Montgomery (209)	55,516,211	18,009,957	73,526,168	92,650,910	79
Morgan (211)	72,438,951	31,656,803	104,095,754	129,816,854	80
Murray (213)	37,095,200	11,344,689	48,439,889	69,130,928	70
Muscogee (215)	33,353,715	12,175,946	45,529,661	56,912,868	80
Newton (217)	56,163,061	8,197,028	64,360,089	74,704,893	86
Oconee (219)	15,965,070	5,162,754	21,127,824	29,312,060	72

Oglethorpe (221)	114,962,343	28,003,613	142,965,956	181,771,401	79
Paulding (223)	71,613,522	21,990,584	93,604,106	115,530,905	81
Peach (225)	18,530,548	3,088,425	21,618,973	25,940,071	83
Pickens (227)	66,742,499	16,278,010	83,020,509	102,602,999	81
Pierce (229)	39,170,167	20,280,572	59,450,739	80,654,426	74
Pike (231)	47,531,903	19,165,214	66,697,117	82,298,299	81
Polk (233)	76,546,823	23,114,365	99,661,188	123,514,242	81
Pulaski (235)	32,955,733	7,984,884	40,940,617	51,937,006	79
Putnam (237)	93,473,195	19,064,357	112,537,552	132,881,181	85
Quitman (239)	32,659,350	12,363,988	45,023,338	65,016,908	69
Rabun (241)	58,054,553	22,923,023	80,977,576	120,779,495	67
Randolph (243)	55,317,136	26,133,903	81,451,039	108,825,753	75
Richmond (245)	45,324,376	23,300,703	68,625,079	85,255,707	80
Rockdale (247)	10,201,084	4,335,513	14,536,597	18,278,008	80
Schley (249)	57,442,157	12,518,356	69,960,513	87,806,350	80
Screven (251)	101,301,540	40,067,685	141,369,225	198,841,718	71
Seminole (253)	5,234,314	1,303,318	6,537,632	13,042,778	50
Spalding (255)	28,955,828	9,604,949	38,560,777	52,990,447	73
Stephens (257)	57,956,616	13,875,460	71,832,076	82,514,458	87
Stewart (259)	130,431,843	50,131,035	180,562,878	217,171,029	83
Sumter (261)	56,098,710	22,257,765	78,356,475	109,641,792	71
Talbot (263)	108,994,276	36,435,952	145,430,228	184,257,951	79
Taliaferro (265)	74,818,595	18,748,716	93,567,311	107,949,818	87
Tattnall (267)	59,076,482	31,972,145	91,048,627	125,671,650	72
Taylor (269)	124,014,715	27,570,600	151,585,315	180,352,520	84
Telfair (271)	140,614,750	40,133,246	180,747,996	217,852,224	83
Terrell (273)	67,051,112	19,489,107	86,540,219	107,789,251	80
Thomas (275)	15,858,031	12,781,432	28,639,463	48,200,692	59
Tift (277)	40,025,487	3,990,035	44,015,522	58,705,478	75
Toombs (279)	58,642,623	15,323,364	73,965,987	96,043,852	77
Towns (281)	10,060,584	6,879,666	16,940,250	28,087,351	60
Treutlen (283)	29,720,783	8,905,644	38,626,427	54,878,671	70
Troup (285)	77,135,167	24,649,831	101,784,998	132,712,273	77
Turner (287)	17,136,382	6,712,311	23,848,693	32,161,500	74
Twiggs (289)	97,425,487	32,736,798	130,162,285	155,656,373	84
Union (291)	55,529,008	19,031,527	74,560,535	97,020,856	77
Upson (293)	80,655,074	20,862,103	101,517,177	127,975,684	79
Walker (295)	108,764,540	18,652,136	127,416,676	152,350,898	84
Walton (297)	33,711,560	8,390,701	42,102,261	57,387,050	73
Ware (299)	171,371,430	72,967,485	244,338,915	307,585,157	79
Warren (301)	67,943,833	20,554,688	88,498,521	119,618,088	74
Washington	111,233,683	35,217,324	146,451,007	201,999,278	73

(303)					
Wayne (305)	104,618,675	38,795,910	143,414,585	200,911,479	71
Webster (307)	45,485,121	7,962,242	53,447,363	60,363,123	89
Wheeler (309)	45,102,375	14,407,966	59,510,341	80,914,489	74
White (311)	35,375,059	13,783,717	49,158,776	67,422,421	73
Whitfield (313)	29,487,632	9,059,469	38,547,101	49,568,993	78
Wilcox (315)	58,462,495	19,039,282	77,501,777	104,899,172	74
Wilkes (317)	118,466,108	36,415,373	154,881,481	202,246,009	77
Wilkinson (319)	126,844,859	35,006,640	161,851,499	197,150,159	82
Worth (321)	51,214,985	13,791,886	65,006,871	85,711,406	76
Totals:	9,609,121,900	3,061,288,922		3,061,288,922	

Basal area (BA) of pre-merchantable trees in selected counties of Georgia

County	BA by Tree Diameter Classification 1.0-2.9 in (1)	3.0-4.9 in (2)	Total BA of PMT	Total BA of all trees	% of the BA of PMT against the BA of all trees
Appling (1)	1,717,628	2,279,110	3,996,738	21,868,160	18
Atkinson (3)	942,452	1,492,260	2,434,712	10,078,836	24
Bacon (5)	728,630	1,888,546	2,617,176	12,262,848	21
Baker (7)	342,062	317,264	659,326	6,977,636	9
Baldwin (9)	1,108,060	1,243,533	2,351,593	11,078,575	21
Banks (11)	696,213	571,882	1,268,095	7,311,891	17
Barrow (13)	332,152	244,390	576,543	4,700,981	12
Bartow (15)	2,569,350	3,038,499	5,607,849	18,260,617	31
Ben Hill (17)	608,428	1,654,667	2,263,095	10,706,077	21
Berrien (19)	2,347,676	2,311,918	4,659,594	15,942,268	29
Bibb (21)	721,252	621,586	1,342,838	6,533,609	21
Bleckley (23)	738,347	822,893	1,561,241	7,481,654	21
Brantley (25)	1,553,081	3,573,401	5,126,481	19,364,098	26

Brooks (27)	1,349,720	1,773,198	3,122,918	14,432,926	22
Bryan (29)	1,209,841	2,047,268	3,257,109	20,808,813	16
Bulloch (31)	2,711,826	2,865,218	5,577,044	26,683,626	21
Burke (33)	2,198,878	3,379,557	5,578,434	33,274,312	17
Butts (35)	898,892	985,519	1,884,411	6,733,339	28
Calhoun (37)	634,624	745,531	1,380,155	6,026,060	23
Camden (39)	2,330,466	3,187,863	5,518,330	27,969,625	20
Candler (43)	962,423	1,136,435	2,098,857	6,910,931	30
Carroll (45)	2,302,939	2,242,382	4,545,321	21,991,871	21
Catoosa (47)	147,967	118,374	266,341	2,672,245	10
Charlton (49)	2,182,448	4,121,755	6,304,203	25,810,504	24
Chatham (51)	640,584	1,222,037	1,862,621	11,921,612	16
Chattahoochee (53)	766,370	1,164,015	1,930,384	10,386,654	19
Chattooga (55)	2,189,630	2,213,178	4,402,808	17,750,677	25
Cherokee (57)	1,222,887	1,330,362	2,553,248	17,249,133	15
Clarke (59)	348,039	299,933	647,972	2,591,302	25
Clay (61)	698,483	822,893	1,521,377	7,076,285	21
Clayton (63)	160,581	112,475	273,056	1,703,883	16
Clinch (65)	3,499,892	7,496,736	10,996,627	41,457,065	27
Cobb (67)	207,483	218,435	425,918	3,525,622	12
Coffee (69)	1,978,022	2,638,056	4,616,078	19,751,422	23
Colquitt (71)	775,107	737,956	1,513,063	11,783,894	13
Columbia (73)	724,126	971,151	1,695,277	10,782,886	16
Cook (75)	923,118	1,162,529	2,085,647	8,704,934	24
Coweta (77)	2,256,026	2,135,815	4,391,841	19,500,055	23
Crawford (79)	1,763,238	2,178,325	3,941,563	12,602,119	31
Crisp (81)	851,030	800,147	1,651,177	6,907,176	24
Dade (83)	322,554	322,014	644,568	7,183,607	9
Dawson (85)	766,352	1,122,499	1,888,851	10,112,519	19
Decatur (87)	1,150,243	1,303,058	2,453,301	13,420,271	18
Dekalb (89)	302,969	282,307	585,276	4,622,455	13
Dodge (91)	2,064,378	2,476,733	4,541,111	20,708,163	22
Dooly (93)	492,366	807,708	1,300,074	7,128,353	18
Dougherty (95)	757,418	542,788	1,300,207	10,738,790	12
Douglas (97)	210,202	494,302	704,505	7,735,148	9
Early (99)	770,585	998,145	1,768,730	12,353,110	14
Echols (101)	2,548,060	4,082,054	6,630,113	19,445,918	34
Effingham (103)	1,909,166	3,068,041	4,977,208	23,420,652	21
Elbert (105)	1,497,570	1,557,022	3,054,592	14,272,375	21
Emanuel (107)	3,051,192	2,990,241	6,041,432	29,331,847	21
Evans (109)	686,349	586,107	1,272,456	8,707,411	15
Fannin (111)	1,563,890	2,012,353	3,576,243	19,934,648	18
Fayette (113)	278,721	270,202	548,923	3,784,803	15

Floyd (115)	1,726,745	2,639,598	4,366,343	19,327,951	23
Forsyth (117)	353,005	384,849	737,854	4,587,741	16
Franklin (119)	359,015	1,347,879	1,706,894	7,733,561	22
Fulton (121)	1,065,220	811,306	1,876,525	14,765,141	13
Gilmer (123)	1,735,856	2,320,378	4,056,234	28,218,130	14
Glascock (125)	887,996	926,722	1,814,719	6,103,463	30
Glynn (127)	1,161,866	1,731,904	2,893,770	12,273,257	24
Gordon (129)	1,091,680	1,183,720	2,275,400	8,701,801	26
Grady (131)	611,585	965,425	1,577,010	11,616,895	14
Greene (133)	2,264,275	3,646,591	5,910,866	21,493,917	28
Gwinnett (135)	905,631	838,865	1,744,496	10,209,972	17
Habersham (137)	627,062	923,348	1,550,410	13,606,211	11
Hall (139)	860,625	1,054,732	1,915,356	9,677,287	20
Hancock (141)	3,107,215	3,592,756	6,699,971	24,792,468	27
Haralson (143)	898,643	961,272	1,859,915	11,764,281	16
Harris (145)	2,170,598	3,656,470	5,827,068	22,900,019	25
Hart (147)	379,776	534,815	914,592	6,153,954	15
Heard (149)	1,321,017	1,875,545	3,196,562	12,012,420	27
Henry (151)	821,352	979,720	1,801,072	10,003,201	18
Houston (153)	519,766	1,042,406	1,562,172	12,059,331	13
Irwin (155)	916,269	853,104	1,769,374	9,273,550	19
Jackson (157)	1,195,325	1,617,106	2,812,431	11,114,810	25
Jasper (159)	2,145,196	2,654,181	4,799,377	21,718,630	22
Jeff Davis (161)	1,268,756	1,968,427	3,237,182	14,643,467	22
Jefferson (163)	1,566,029	2,880,454	4,446,483	20,732,854	21
Jenkins (165)	1,345,993	1,098,054	2,444,047	10,747,880	23
Johnson (167)	1,021,554	826,271	1,847,825	10,883,032	17
Jones (169)	2,754,161	2,929,795	5,683,955	19,239,519	30
Lamar (171)	1,402,162	970,971	2,373,133	7,771,919	31
Lanier (173)	838,471	1,468,431	2,306,902	7,732,909	30
Laurens (175)	3,394,478	3,992,290	7,386,768	31,980,782	23
Lee (177)	590,941	638,129	1,229,070	9,422,750	13
Liberty (179)	1,660,577	1,574,742	3,235,319	22,061,455	15
Lincoln (181)	1,248,562	861,395	2,109,957	9,930,797	21
Long (183)	2,497,874	2,520,315	5,018,188	21,390,239	23
Lowndes (185)	2,137,232	1,936,541	4,073,773	15,259,272	27
Lumpkin (187)	897,667	1,341,568	2,239,236	17,285,494	13
McDuffie (189)	881,829	1,602,436	2,484,265	12,282,024	20
McIntosh (191)	1,594,322	1,417,059	3,011,381	15,022,435	20
Macon (193)	1,708,959	1,272,335	2,981,294	13,696,996	22
Madison (195)	747,251	1,237,763	1,985,014	8,210,365	24
Marion (197)	1,155,811	1,871,585	3,027,396	12,423,662	24
Meriwether (199)	2,589,904	2,968,950	5,558,854	22,535,600	25

Miller (201)	610,065	544,729	1,154,794	5,866,275	20
Mitchell (205)	633,950	1,318,005	1,951,955	10,073,280	19
Monroe (207)	1,928,051	1,519,686	3,447,738	18,599,794	19
Montgomery (209)	1,211,142	1,571,621	2,782,763	11,207,396	25
Morgan (211)	1,580,328	2,762,499	4,342,827	16,140,583	27
Murray (213)	809,269	989,983	1,799,252	11,978,884	15
Muscogee (215)	727,645	1,062,522	1,790,166	6,644,553	27
Newton (217)	1,225,253	715,305	1,940,559	9,203,000	21
Oconee (219)	348,294	450,523	798,817	5,522,269	14
Oglethorpe (221)	2,508,018	2,443,707	4,951,726	23,603,254	21
Paulding (223)	1,562,321	1,918,986	3,481,307	13,815,746	25
Peach (225)	404,262	269,508	673,771	2,533,267	27
Pickens (227)	1,456,054	1,420,484	2,876,539	13,037,690	22
Pierce (229)	854,536	1,769,764	2,624,300	11,387,487	23
Pike (231)	1,036,956	1,672,433	2,709,389	10,441,809	26
Polk (233)	1,669,945	2,017,052	3,686,997	13,986,168	26
Pulaski (235)	718,962	696,793	1,415,755	6,548,959	22
Putnam (237)	2,039,211	1,663,632	3,702,843	12,558,646	29
Quitman (239)	712,496	1,078,931	1,791,427	9,684,075	18
Rabun (241)	1,266,518	2,000,355	3,266,873	26,748,924	12
Randolph (243)	1,206,799	2,280,549	3,487,348	15,091,688	23
Richmond (245)	988,797	2,033,313	3,022,109	11,156,422	27
Rockdale (247)	222,547	378,334	600,881	2,872,018	21
Schley (249)	1,253,158	1,092,402	2,345,560	8,433,148	28
Screven (251)	2,209,994	3,496,466	5,706,461	32,564,451	18
Seminole (253)	114,192	113,733	227,925	2,987,289	8
Spalding (255)	631,700	838,166	1,469,867	9,280,346	16
Stephens (257)	1,264,382	1,210,828	2,475,210	7,935,043	31
Stewart (259)	2,845,501	4,374,635	7,220,136	19,485,811	37
Sumter (261)	1,223,849	1,942,302	3,166,151	15,896,915	20
Talbot (263)	2,377,819	3,179,547	5,557,366	19,489,037	29
Taliaferro (265)	1,632,242	1,636,088	3,268,330	9,283,699	35
Tattnall (267)	1,288,813	2,790,017	4,078,830	17,843,844	23
Taylor (269)	2,705,505	2,405,921	5,111,426	16,163,647	32
Telfair (271)	3,067,651	3,502,188	6,569,839	21,834,178	30
Terrell (273)	1,462,787	1,700,697	3,163,484	12,403,272	26
Thomas (275)	345,959	1,115,359	1,461,318	13,039,400	11
Tift (277)	873,196	348,186	1,221,382	9,321,120	13
Toombs (279)	1,279,347	1,337,178	2,616,525	12,112,052	22
Towns (281)	219,482	600,347	819,829	6,725,997	12
Treutlen (283)	648,389	777,142	1,425,531	9,096,455	16
Troup (285)	1,682,781	2,151,043	3,833,824	18,454,568	21
Turner (287)	373,847	585,743	959,590	4,148,530	23

Twiggs (289)	2,125,434	2,856,744	4,982,178	16,287,202	31
Union (291)	1,211,421	1,660,767	2,872,188	15,732,148	18
Upson (293)	1,759,571	1,820,511	3,580,082	15,860,523	23
Walker (295)	2,372,807	1,627,660	4,000,467	17,276,311	23
Walton (297)	735,451	732,206	1,467,658	11,935,870	12
Ware (299)	3,738,639	6,367,435	10,106,074	30,635,798	33
Warren (301)	1,482,263	1,793,684	3,275,947	16,792,694	20
Washington (303)	2,426,674	3,073,205	5,499,879	26,629,832	21
Wayne (305)	2,282,361	3,385,486	5,667,847	28,041,282	20
Webster (307)	992,303	694,817	1,687,120	4,671,169	36
Wheeler (309)	983,953	1,257,297	2,241,250	14,009,879	16
White (311)	771,742	1,202,822	1,974,565	11,879,083	17
Whitfield (313)	643,302	790,566	1,433,868	8,025,992	18
Wilcox (315)	1,275,418	1,661,444	2,936,862	15,160,366	19
Wilkes (317)	2,584,457	3,177,751	5,762,208	24,721,051	23
Wilkinson (319)	2,767,247	3,054,819	5,822,067	23,161,266	25
Worth (321)	1,117,306	1,203,535	2,320,841	13,789,348	17
Totals:	15,731,699,744	28,402,110,566	28,402,110,566	44,133,810,310	