THE ESTIMATION OF PINE TIMBER VOLUME USING LANDSAT THEMATIC MAPPER SATELLITE DATA

by

Roger Charles Lowe III

(Under the direction of Dr. Chris Cieszewski)

ABSTRACT

The First and Second Blue Ribbon Panels on Forest Inventory and Analysis voice the need for improving the sampling and analysis methods used to generate reports on the welfare our Nation's timberlands. The panelists note that the use of aerial photography for certain measurements and stratification for field sampling is too labor-intensive, and that satellite remote sensing can improve the inventory process. They suggest that satellite remote sensing should be implemented wherever it will lead to improved efficiency.

In an attempt to demonstrate the utility of Landsat Thematic Mapper (LTM) satellite data in a large-scale inventory, a study was conducted in western Georgia to evaluate the relationship between "leaf-off" and "leaf-on" LTM data and coniferous stand parameters. Linear regression models applied to an independent dataset yielded significant results in which basal area was estimated within +/- 19%, and volume was estimated within +/- 28% of the ground measurements.

INDEX WORDS: Landsat Thematic Mapper, Remote sensing, Forest Inventory & Analysis, Forestry, Volume, Basal area

THE ESTIMATION OF PINE TIMBER VOLUME USING LANDSAT THEMATIC MAPPER SATELLITE DATA

by

Roger Charles Lowe III

B.S.F.R., The University of Georgia, 1996

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2002

THE ESTIMATION OF PINE TIMBER VOLUME USING LANDSAT THEMATIC

MAPPER SATELLITE DATA

by

Roger Charles Lowe III

Approved:

Major Professor: Dr. Chris Cieszewski

Committee: Dr. Bruce Borders
Dr. Robert Cooper

Electronic Version Approved:

Gordhan L. Patel
Dean of the Graduate School
The University of Georgia
August 2002

DEDICATION

This paper is dedicated to the most wonderful wife I could have ever asked for. Baby, I could not have made it through the last 4 years without you.

ACKNOWLEDGMENTS

Dr. Chris Cieszewski was instrumental in helping me see this project to the end. I thank him for his dedication and insight.

TABLE OF CONTENTS

I. BACKGROUND

For more than a century, the United States Congress has recognized the importance of our Nation's timberlands, and the need for a structured national timberland inventory. Congress initiated establishment of the forest reserves from timber-covered, public domain land with the Forest Reserve Act of 1891. Soon after this bill was signed, several million acres of land in the West were designated as forest reserves.

Our National Forest System and additional criteria for new forest reserve lands were established with the Organic Act of 1897. It required that new reserve lands must be able to (1) improve and protect the forest within the boundaries, (2) furnish a continuous supply of timber for the use and necessities of the citizens of the United States, and (3) secure favorable conditions of water flow. The Organic Act also required that the millions of acres of forest reserve be managed by "on-the-ground" forest rangers. Those early forest rangers were the predecessors to our modern-day United States Department of Agriculture Forest Service (USFS), 1905 - present.

The USFS organized regional forest survey projects in response to the McSweeney-McNary Act of 1928. A network of 12 regional experiment stations were established throughout the country. Later, these stations would become the backbone of the USFS' research effort. The Act also directed the Secretary of Agriculture to prepare and maintain an inventory and analysis of the Nation's forest resources. This was the beginning of the national inventory system and the predecessor to today's Forest Inventory and Analysis (FIA) program.

The Multiple-Use Sustained-Yield Act of 1960 established the management criteria on which many of today's guidelines are based. The Multiple-Use Sustained-Yield Act states that "the national forests are established and administered for outdoor recreation, range, timber, watershed, and wildlife and fish purposes" ([16 U.S.C. 528]). Included in their definition of multiple-use are all renewable surface resources of the national forests. Further more, the Act requires those renewable surface resources be "utilized in the combination that will best meet the needs of the American people" ([Section 4, paragraph a [16 U.S.C 531]). To satisfy these criteria, the forest managers of our forests are charged with the goal of achieving and revising when needed a periodic survey of those renewable resources of the national forests.

Building on the notion of making and keeping a current and comprehensive inventory brought forth in the McSweeney-McNary Act of 1928, the Resources Planning Act of 1974 required the Secretary of Agriculture to develop, maintain, and revise a land and resource management plan for the National Forest System (Section 6 [16 U.S.C. 1604]). Supporting this Act, the Resources Planning Act of 1978 directed the Secretary of Agriculture to survey and produce periodic analyses of the present and prospective conditions of the forests and rangelands of the United States. The reports were to include a determination of the present and potential productivity of the land and any other facts that may be necessary to balance the demand for and supply of the renewable resources in question (16 U.S.C. 1642]).

The guidelines by which we measure our Nation's timberland and manage it for multiple uses are continually being revised by legislative mandates. The Agricultural Research, Extension, And Education Reform Act of 1998, also referred to as the Farm

Bill, addressed the need for a more timely inventory and analysis of our public and private forest resources. Realizing this need, Congress mandated that, by 2003, 20% of all FIA sample plots in each state be measured annually. Also acknowledged in the Farm Bill was the need for exploring possible uses of remote sensing and other advanced technologies to expedite field measurements and increase the accuracy of forest metrics.

A. National Inventory

Including our National Forests, our Nation's timberlands encompass more than 747 million acres. Mandated by Congress to make and keep current an inventory and analysis of the current and future natural resources, the USFS implemented the FIA program in 1930. In its current format, the program collects, analyzes, and reports information on the status and trends of America's forests. The program includes all public and private forest lands including reserved areas, wilderness, National Parks, defense installations, and National Forests in all 50 states and territories and possessions of the US.

Per guidelines established in the Farm Bill, the USFS is required to be on a schedule to annually measure 20% of the permanent sample plots in each state by 2003. At each sample plot, a set of core ecological and physical plant and site variables are to be recorded. The data will then be compiled, analyzed, and reported by the USFS each year. On a five-year cycle, a complete analytical report containing the

(1) current status of the forest for the last 5 years;

(2) trends in forest status and condition over the preceding twenty-years;

(3) timber product and output, and

(4) analysis of the probable forces causing the observed conditions.

A projection of the likely trends in key resource attributes over the next twenty-years is produced as well.

Considering the immense task of inventorying and reporting on the many acres of forest, our natural resource managers need to, and many have already, realize the need for improving the sampling and analysis methods used to obtain the timberland metrics in an accurate, localized, and timely manner. According to a report issued by the committee on the Environment and Natural Resources titled, "Integrating the Nation's Environmental Monitoring and Research Networks and Programs: A Proposed Framework", concerns about the state of America's timberlands have led to a "widespread perception that existing monitoring efforts and capabilities, characterized by a decentralized set of programs that rely on ground and aerial observations, are failing to meet increasingly complex and large-scale forest management needs." The report reiterated several concerns voiced in the First and Second Blue Ribbon Panels on Forest Inventory and Analysis:

(1) the U.S. lacks a national and timely forest database, and

(2) the use of aerial photography for certain measurements and stratification for field sampling is too labor-intensive.

Their recommendations for improving the current FIA program include

(1) making the integration of environmental monitoring and research networks and programs across temporal and spatial scales top priority;

(2) increasing the use of remotely sensed information for detecting and evaluating environmental status and change;

(3) evaluating alternative methods of stratification based on variables such as ecoregion, known and anticipated environmental stresses, location along environments gradients, and unique aspects of terrestrial and hydrological ecosystems;

(4) using data from resources inventories and remote sensing for characterizing and detecting changes at index sites;

(5) establishing a geo-referenced database of ongoing environmental monitoring programs, and

(6) disseminating all framework information and data in a timely manner.

B. FIA Program Description

Realistically, by 2003, the USFS hopes to be on a schedule to sample 15% of the FIA phase II and 20% of the phase III points annually (Dombeck 2000, Table 1.1). Originally, the plots were sampled using a 2-phase systematic sample, a photo interpretation phase and a ground measurement phase. Due to Congress' demand for a merger with the Forest Health Monitoring (FHM) program, a third phase has been added which includes the FHM measurements on a subset of the phase 2 plots.

Table 1.1 Mandated and realistic FIA Cycles

	East Phase II	East Phase III	West Phase II	West Phase III
Congress	20%	20%	20%	20%
USFS	15%	20%	10%	20%

Forest/nonforest proportions are computed in phase 1. Points are overlain on analog aerial photographs, approximately one for every 240 acres, and characterized as either being forested or nonforest. Forested strips must be at least 120 feet wide with a minimum area considered for classification of one acre. Two subsets of the photo-interpreted points are then taken. One is used for phase 2 sampling, and the other is ground verified and used to correct the calculated forest/nonforest proportions. Ground verification of the second subsample is important because the photos being used may be old and possibly out-dated (USDA Forest Service 2001).

Forested plots are installed in phase 2, formerly known as the FIA field plots. These plots, approximately 1 for every 6000 acres, are installed and measured regardless of intended use or any restrictive management policy, and on all ownerships. Tree information such as forest type, tree size, tree species, and overall tree condition are measured, as well as, plot specific information like horizontal distance to urban and agricultural land and the GPS coordinate of the plot center are measured (USDA Forest Service 2001). Appendix A contains a list of all items recorded during the Phase II samples.

Phase 3 measurements, formerly the FHM plots, are installed on a 1/16th subset of the phase 2 FIA grid plots. They are surveyed for information about forest ecosystem function, condition, and health. Ozone bioindicators, lichen community samples, soil measurements, crown condition classes, down woody debris and fuel measurements, and diversity and structure measurements are made in this phase (FIA Plot Layout Explanation).

In the proposed 2002 federal budget, the president included $32,498,000 for the USFS research portion of the FIA program. Including an expected $14,010,000 in additional funding, they have $46,508,000 earmarked for fiscal year 2002 - 2003. This is about $10,200,000 below the amount requested by the USFS (Dombeck 2000).

Compounding problems due to an under funded budget, the program must strive to meet the goals set forth in the Farm Bill. On a national level, the FIA program installed a total of 28,349 phase II and III plots during 2000 (October 1, 1999 - September 30, 2000) at an average cost of $1,393 per plot (Gillespie 2000). Of those plots sampled, 11,582 were forested phase II plots which cost an average of $3,833 per plot to install. To reach the goal set by the USFS of sampling 10% of the FIA plots in the west and 15% in the east (Dombeck 2000), a total of 42,464 plots, an increase of 14,115, must be sampled. Assuming the same ratio of sampled forested to non-forested plots, a total of 17,336 forested plots will have to be installed, an increase of 5,754 plots from year 2000. Under the current proposed level of funding, to reach their goal, they must either solicit funding from other sources, or find ways to decrease the cost of installing the FIA sample plots.

There is interest by the USFS to incorporate remotely sensed data into the FIA inventory process to reduce inventory costs and cycle time, and increasing the consistency of the data collected and reported (Czaplewski 1998). Studies by Lashbrook *et. al.*(2001), Vogelman (1990), Evans (1994), and Trotter (1997) have shown that it is possible to incorporate remotely sensed data into large-scale inventories at a decreased cost, though most of the success has been in forested area estimates and landcover type stratification. The ability to estimate FIA ground-measured stand parameters using remotely sensed data will enable updates of forest information during an off-cycle year and would provide another method of stratification.

II. OBJECTIVES

Since the first known photograph was captured over Bievre, France (Lillesand 1994), we have learned much regarding the use of remotely sensed data in natural resource management. It is common practice for forestry companies to incorporate information culled from aerial photos of their lands. In the last 20 years since satellite borne remote sensing data has been publicly available, resource managers have struggled to use the information to its potential. Though they have been used as a base dataset like aerial photographs and to create general landcover classifications, we have yet to fully incorporate satellite data as a common means to measure stand parameters such as basal area and volume.

The objective of this research is to extend the FIA remote sensing functionality by including an ability to estimate coniferous basal area and volume using only Landsat Thematic Mapper (LTM) satellite data with an operationally acceptable accuracy. Common questions regarding the feasibility of using satellite-borne remotely sensed data to estimate specific stand parameters I will address are:

(1) Is satellite data from one season more useful than the other?

(2) What band or combination of bands are most useful?

(3) Can one obtain volume estimates using only LTM data at the same level of accuracy the FIA program requires?

I will compare basal area and volume measurements from sample plots established throughout western Georgia and eastern Alabama to Landsat Thematic

Mapper satellite data captured in leaf-off and leaf-on conditions. Various combinations of LTM data from two different seasons will be evaluated for basal area and volume predictive ability. Winter, summer, and winter and summer models will be assessed for seasonal differences among the LTM data with respect to stand parameter estimation. Those seasonal variables deemed significant will be reported. Finally, I will document the methods by which LTM-derived information can be incorporated into the FIA program and demonstrate LTM's volume estimation ability by comparing LTM-derived volume estimations with FIA volume estimations over a subset of Georgia counties.

III. REVIEW OF REMOTE SENSING TECHNOLOGY

Aerial photography is believed by many to have its beginnings in 1858, when Gaspard Felix Tournachon, a Parisian photographer, used a balloon to take a photograph of Bievre, France (Lillesand 1994). Two years later, the earliest existing aerial photograph was taken from a balloon over Boston by James Wallace Black (Lillesand 1994). These photographs finally allowed the public to see the world "... as the eagle and the wild goose see it ..." (Oliver Wendell Holmes, Atlantic Monthly, July 1863).

The first photograph taken from an airplane was not until 1909 when a movie photographer captured a motion picture while accompanying Wilbur Wright on a flight in Centocelli, Italy (Lillesand 1994). As early as the 1920's, foresters used aerial photography interpretation to create cover type maps and land type area estimates. In the 1930's, the USFS used aerial photographs in its land acquisition work and to map the Tennessee Valley (TVA 2002). Though airplane photography was much less cumbersome than balloon and kite photography, it did not gain wide use until the US Department of Agriculture's Agricultural Stabilization and Conservation Service began photographing selected counties of the United States, and in World War II when the military began aerial photo reconnaissance (Lillesand 1994).

By the 1960's, the ability to acquire information about those resources under management using aerial photography was an invaluable tool for a majority of forest industry companies in the South. It was estimated that in 1969 and 1970 that 82% of the industrial holdings in the South, 33-million acres, were in some way managed using aerial photography (Baker 1970). Those management tasks included timber procurement, timber stand mapping, reforestation planning, and road and property line location to name a few. Aerial photography also proved useful for other tasks like landcover change analysis (Meyer 1981), individual tree mapping, timber volume estimation (Williams 1978), and tree pest and disease mapping (Heller 1973). Today, though mostly in digital format, aerial photography is still being used for many of the same tasks (Wagner 1997, Wilson 1995).

Though aerial photography is still widely used in many natural resource disciplines, there are disadvantages to using aerial photographs in vegetation monitoring. Aerial photographs have a relatively small instantaneous field of view. A 9-inch by 9-inch aerial photograph at a scale of 1:40,000 covers approximately 20,600 acres. For multi-county and state inventories, many photographs are required. This leads to the next disadvantage - the cost. Depending on the size of the photo mission, the cost may range anywhere from $0.25 per acre up to $0.50 per acre for color photos, and more for color-infrared photos. A third shortcoming is inconsistency in the air photo interpretation process itself. It is unlikely that two people will interpret a photograph exactly the same. This is compounded by the fact that similar features between and within photographs may appear different in tone and texture usually caused different levels of illumination and shadowing. Finally, the geometric properties of an aerial photograph are not consistent throughout the photo. Taking elevational changes into consideration, the scale of the photograph is most accurate in the area that was directly below the camera. As you progress outward towards the edges of the photograph, the accuracy of the scale decreases (Lillesand, 1994).

Many of the drawbacks associated with aerial photography can be minimized by implementing digital images captured by satellite-borne remote sensing systems. LTM scene dimensions are 115 miles by 115 miles - almost 8.5 million acres (Landsat TM Metadata). Four-hundred and ten aerial photographs at a scale of 1:40,000 would be required to cover the same area of one LTM dataset. LTM scenes can be purchased from the EROS Data Center (http://edcwww.cr.usgs.gov) for $425 a scene, or approximately $0.05 per 1000 acres. While many of the digital image classification routines require user input, much of the processing can be automated which eliminates much of the subjectiveness present in aerial photo interpretation. LTM images are snap-shots of a relatively large area of the Earth's surface at one point in time. Confusion present in aerial photo interpretation due to illumination and shadowing differences caused by different times of day are minimized. Finally, the geometric properties present in aerial camera systems do not apply to the LTM sensor. Taking elevational changes into consideration, the images have a constant scale throughout.

A. The Landsat Program

The Landsat program, currently under the control of NASA and the Department of Defense, has been operating since the early 70's. The project was originally proposed by scientists and administrators in the U. S. Government with the objective of evaluating the technology involved in space-borne remote sensing of the Earth's resources. Today, the data captured by Landsat-1 through -5 and -7 provide the basis for detailed, repetitive, and synoptic mapping and analysis of the Earth's structures.

LTM-5 has onboard a 7-channel scanning radiometer calibrated to record reflected energy from the Earth's surface in 7 distinct portions of the electromagnetic spectrum. The electromagnetic spectrum, as we "see" it with our own eyes, consists of light ranging from violet to red. These visible colors represent a small portion of the spectrum ranging from ~ 0.400 to ~ 0.700 micrometers. The spectrum extends further above and below the visible wavelengths. Gamma, X-, and ultraviolet rays all have shorter wavelengths than the visible portion of the spectrum (~10^-11 ~0.1 micrometers). Infrared light, microwaves, and radio waves are located in the long wavelength, lower energy portion ranging from approximately 1 to 10^8 micrometers (Figure 3.1).

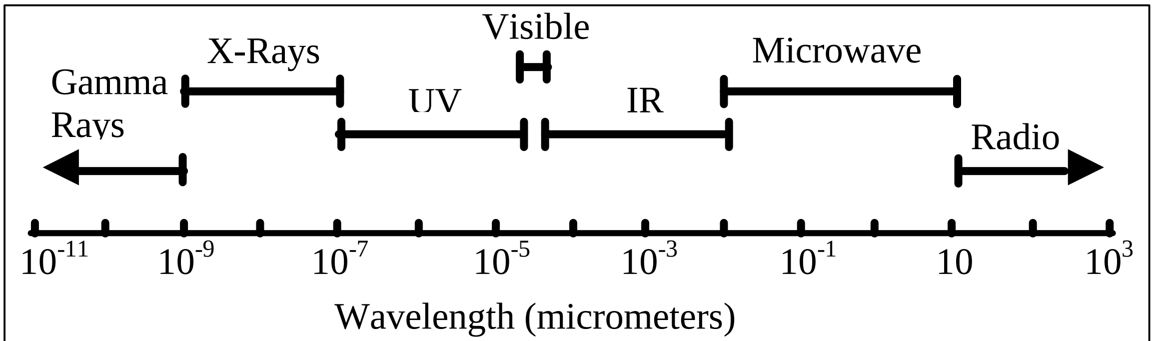

Figure 3.1 The Electromagnetic Spectrum

The recorded reflectance values from each channel is converted to 8-bit data (256 "shades of gray"), which are referred to as a "digital numbers" (DN) instead of reflected energy. The resulting product is a 7-layer dataset in which each layer contains DN information from different portions of the spectrum. Layers 1 - 5 and 7 have a 30-meter ground resolution, and layer 6 has a 120-meter resolution.

The portion of the spectrum sensed by each band was selected to maximize the discrimination and monitoring of different types of resources on the Earth's surface.

Channel 1 (TM1), the "blue band", has been applied in coastal water mapping and differentiating between vegetation and soil. Channel 2 (TM2), the "green band", is sensitive to green reflectance from healthy vegetation which aides the assessment of vegetation vigor. Chlorophyll absorption in vegetation is recorded in channel 3 (TM3), the "red band". TM3 is helpful in discriminating different types of vegetation. In coniferous forests, reflectance in TM1 - TM3 has been found to be inversely related to basal area and biomass (Coops 1998). The "near-infrared band", channel 4 (TM4), is a moisture-sensitive band. TM4 is ideal for detecting near-infrared reflectance peaks in healthy green vegetation, and the detection of water bodies. Channel 5 (TM5), the "shortwave near-infrared band", is suitable for detecting vegetation and soil moisture, differentiation of snow and clouded areas, and for discriminating between rock and mineral types. It is sensitive to vegetation density and canopy shading and leaf moisture (Coops 1998). The "thermal band", channel 6 (TM6), is designed to assist in thermal mapping, soil moisture studies, and plant stress measurements. Channel 7 (TM7), referred to as the "far mid-infrared band", is ideal for vegetation and soil moisture studies, discriminating between rock and mineral types, and urban change studies (Table 3.1, GeoScience Australia 2002, Landsat TM Metadata).

Table 3.1 Landsat Thematic Mapper Band Description

Band	Wavelength (micrometers)	Application(s)
TM1 "Blue"	0.45 - 0.52	coastal and vegetation / soil mapping
TM2 "Green"	0.52 - 0.60	assessing vegetation vigor
TM3 "Red"	0.63 - 0.69	vegetation discrimination, chlorophyll absorption
TM4 "NIR"	0.76 - 0.90	high moisture absorption band
TM5 "SWIR"	1.55 - 1.75	detecting vegetation and soil moisture
TM6 "TIR"	10.40 - 12.50	thermal mapping
TM7 "FMIR"	2.08 - 2.35	detecting vegetation and soil moisture

B. Desirable Remotely Sensed Characteristics

Scientists working on the Coastal Change Analysis Program (C-CAP), pointed out several satellite sensor-related characteristics one must consider before their incorporation into a management regime. The first factor is the sensor's temporal resolution. Temporal resolution refers to the time it takes to capture an image over the same area (e.g. LTM path 17, row 37) . The LTM-5 satellite has a 16-day repeat cycle, which lends itself well to landcover change and vegetation monitoring studies. The spatial resolution, the area that one pixel in the image represents on the ground, is the second factor one must consider. While the LTM sensor does not have the lowest spatial resolution available on the market, 30-meters, it is suitable for vegetation monitoring and mapping (Evans 1994). The minimum mapping unit (MMU) must be considered as well. The MMU is defined as the smallest group of objects on the ground that will be considered in the analysis - the smallest area you want to describe. If using only LTM-5 data, due to its 30-meter spatial resolution, the smallest possible mmu is 30 square-meters. Spectral resolution is the final consideration the C-CAP scientists pointed out. It refers to the portion(s) of the electromagnetic spectrum recorded by the remote sensing platform. The LTM sensor has a medium spatial resolution, recording energy in 7 regions of the spectrum. For a landcover classification and change study to be successful, the spectral resolution must be fine enough to record unique spectral attributes, signatures, of the objects of interest on the ground. The ideal sensor for landcover studies hold all 4 of these characteristics constant throughout the images and between different images captured on the same date as well as from images captured on different dates.

IV. REMOTE SENSING AND TIMBER BIOMASS ESTIMATION

One way to increase the timeliness and accuracy of our national inventory is by the incorporation of remotely sensed imagery (Czaplewski 1998). Lashbrook *et al*. (2001) realized in their inventory of white pine in eastern Ohio, that a LTM-based inventory required less labor and time than traditional inventories while yielding estimates with standard errors substantially below those of existing inventories. Others have acknowledged that LTM data has a resolution appropriate for vegetation mapping (Evans 1994) and is a data source from which acceptable estimates over large areas are possible (Trotter 1997).

The information content of a Landsat Thematic Mapper (LTM) satellite image is immense; recording spectral information in six visible and one thermal band of the electromagnetic spectrum. Since unlike materials absorb radiation at different rates along different portions the electromagnetic spectrum, targets on the ground can often be differentiated by their spectral reflectance signature. Thus, it is necessary to determine the information content and reduce the dimensionality of the LTM dataset before we can develop application-specific models. Statistically-based routines like principal components and regression, as well as computer-aided image classification have been used to both reduce the dimensionality and assess the information content of LTM imagery.

Horler and Ahern (Horler 1986) investigated the potential for using principal components analysis to discriminate general cover types (clearcuts, burns, spruce, pine, hardwoods, crops, and water) and cover types within a predominantly softwood grouping (spruce and Jack pine) of different ages. Using principal components analysis on a winter LTM image, TM4 and TM5 loaded heaviest on the first principal component. The first component was considered a "brightness" index which was related to the overall reflectance of the pixel. Principal component 2 contrasted the visible bands and the near-infrared band. This yielded a "greenness" index that was correlated with the presence and density of green vegetation. The results of the analyses of the softwood grouping differed only in the fact that TM1 loaded heaviest on the second principal component.

These results suggest that TM4 and TM5 may be useful in discriminating forested and nonforested areas, a combination of the visible and near-infrared bands might be useful in discriminating between general landcover types, and TM5 may possibly lend insight into the differentiation of a more specific landcover classification. These results verify the studies conducted by Crist & Cicone (1984) who, through studies with simulated data, verified that the Tasseled Cap transformation (Kauth 1976) holds true for LTM data. They have shown a correlation between the first three principal components and biological factors on the ground. The first principal component, the "brightness" index, was shown to be a weighted sum of all bands - the overall brightness - where vegetated areas have a low overall reflectance and unvegetated areas have a high reflectance. The "greenness" portion, the second principal component, described the contrast between the near-infrared and the visible bands. This is primarily due to the relatively low reflectance of green vegetation in the visible spectrum and high reflectance of green vegetation in the near-infrared wavelengths. The third principal component, the "wettness" index, contrasts the soil-moisture sensitive band TM5 with the visible and near-infrared band.

Several studies have shown Landsat Thematic Mapper satellite data to be highly correlated with leaf area index (LAI) (De Jong 1994, Nemani 1993, Brown 2000). De Jong, Nemani, and Brown all found strong correlations between the simple ratio (SR), equation [4.1] and the normalized difference vegetation index (NDVI, equation [4.2]) and LAI, the leaf area per unit ground area (Franklin 2001).

$$SR = (NIR / RED) \tag{4.1}$$

$$NDVI = (NIR - RED) / (NIR + RED) \tag{4.2}$$

Rates of photosynthesis, transpiration, evapotranspiration, and nitrogen transformation depend heavily on LAI (Franklin 2001). Both SR and NDVI are based on ratios of red and near-infrared reflected radiation. These vegetation indices are driven by the physical properties of the foliage being sensed. Due to the high red energy absorption of chlorophyll, green leaves reflect relatively little radiation in these wavelengths. Conversely, the lignin component of the plant cell walls absorb small amounts of near-infrared radiation, yielding relatively high amounts of reflected radiation (Turner 1999, De Jong 1994). Turner (1999) and De Jong (1994) both found that areas with a low LAI have relatively high amounts of RED reflectance and relatively low amounts of NIR reflectance. In areas with a high LAI, they found high NIR reflectance and low RED reflectance.

Though success in classifying landcover type is common, and high correlations between LAI and LTM-derived vegetation indices have been realized, estimation of stand parameters like basal area and volume has, for the most part, been limited. Using a "leaf-off" image, Trotter et al (1997) found a "weak but significant" relation between wood volume and LTM reflectance in forests in New Zealand. Using simple linear regression, they found that TM3 was the single band that was most correlated with timber volume (R^2 0.21). The combination of TM3 and TM4 yielded significant results, as did the combination of all spectral bands. Franklin *et. al.* (1986), on a study site in northern California, was able to estimate coniferous timber volume using "leaf-on" LTM data and digital elevation models within 6% of the values obtained by the USFS who used traditional methods. The Batemans Bay, Austrailia (Coops 1998) study had limited success estimating Eucalypt forest basal area using "leaf-off" LTM imagery with R^2 values between 0.24 and 0.29 when the entire study area was considered. Best results, though, were obtained when the study site was stratified by disturbance level. Individual analysis of the sites with "minor" and "major" disturbances resulted in R^2 values of 0.30 and 0.62 respectively. Another "weak but significant" correlation between pine plantation basal area and LTM was obtained in a North Carolina study conducted by Brockhaus *et. al* (1992). Using a "leaf off" LTM image, their regression analysis resulted in an R^2 of 0.23. They concluded that the green, red, near-infrared, and 2 short-wave infrared bands (TM2, TM3, TM4, TM5, & TM7) were significantly correlated with conifer basal area, with TM7 having the highest correlation. Though, they did not try to model the relationship because of the low basal area - Landsat TM correlations.

In an effort to create continuous maps of forest attributes, researchers at the Northeastern Research station (King, 2000) explored the possibility of using kriging to map basal area and cubic-foot volume by incorporating a "leaf-on" LTM image with the 1998 FIA inventory of Connecticut. Of the variables they analyzed, NDVI had the highest individual correlation with cubic-foot volume and basal area, 0.41589 and 0.47829, respectively. Though, the overall highest volume and basal area classification accuracies from the kriging methods were observed using LTM band 4, 80.8% and 67.92%, respectively.

None of these studies found a very high correlation between LTM data and stand parameters, though several trends were apparent. An inverse relationship between reflectance and the amount of vegetation was evident in all visible bands (TM1 - TM3) and short-wave infrared bands (TM5 & TM7) (Horler 1986, Jakobauskas 1994, Vogelman 1990, Trotter 1997; Brockhaus 1992). This trend was also apparent in low-density versus high-density stands (Horler 1986). Jakobauskas & Price (1994) found that the rate of change of this relationship decreases as the stands progress into later successional stages. While studying Fir waves in New Hampshire, Vogelman *et. al.* (1990) found that the mean pixel values in TM3 and TM5 were higher in areas with high mortality while LTM band 4 values were lower.

V. DATA

The study site boundary for this project corresponds with LTM image path 17, row 37 (UL: 85:56:25.5 W, 34:03:33.0 N; LR: 83:32:45.0 W, 32:18:10.0 N) (figure 5.1).

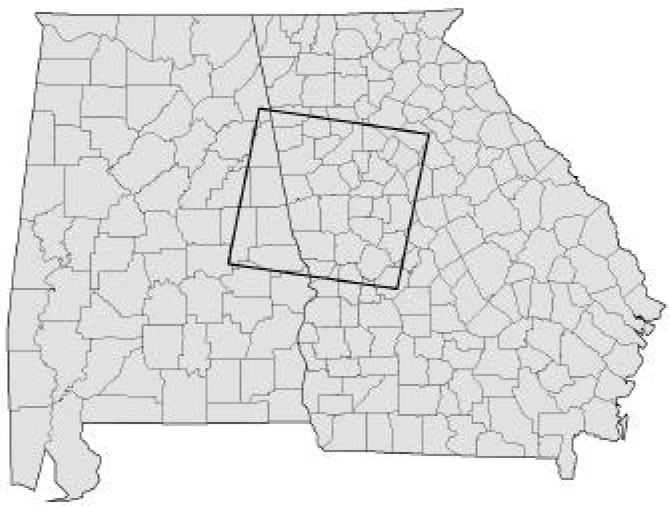

Figure 5.1 Western Georgia and Eastern Alabama Study Area

The LTM image encompasses all or portions of thirty-seven Georgia counties and 10 Alabama counties in the Piedmont physiographic region. This scene is dominated to the north by Atlanta and surrounding urban areas, West Point lake to the southwest, and a mix of conifer, deciduous, and agricultural fields elsewhere. Both the winter scene, captured on November 17, 1997, and the summer scene, captured on May 12, 1998, are virtually cloud-free.

Field data collection occurred over two summers. As a part of the Traditional Pulp and Paper Production (TIP3) project "Quantifying Future Timber Supply:

Developing a Localized, Accurate, Timely and Cost Effective Forest Area Estimation Method, 1999 - 2001", F&W Forestry Services collected ground data from 908 plots in eight counties in western Georgia and eastern Alabama in the summer of 1999 (Figure 5.2).

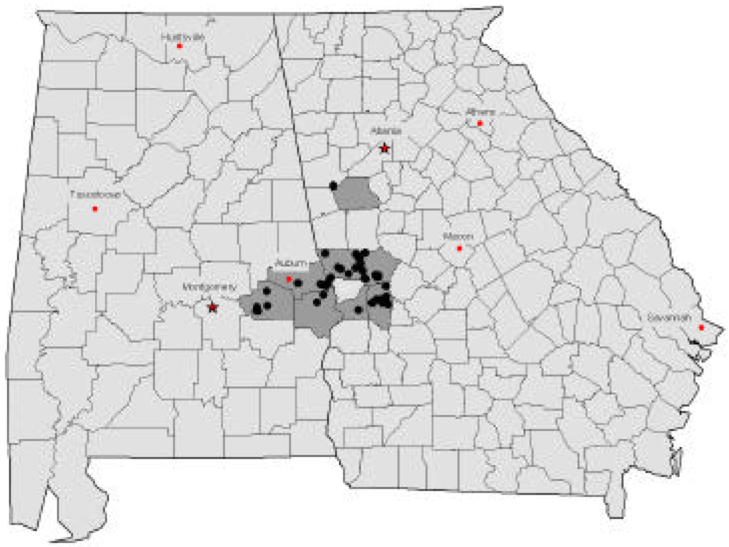

Figure 5.2 Study Area Counties and Plots

Stand types sampled include sapling and mature natural and planted pine stands, unthinned and thinned old field pine stands, sapling and mature upland and bottomland hardwood stands, and pasture and cultivated fields.

In the summer of 2000, funded by the same TIP3 project, a field crew from the Daniel B. Warnell School of Forest Resources installed 284 plots throughout 4 western Georgia counties (figure 5.2). Stand types sampled in this cruise focused on mature natural and planted pine types. A majority of the sample sites from both data collection seasons were collected on TIP3-cooperator land, mainly Mead Coated Board. Several natural pine plots were installed on land managed by Temple-Inland, and the remaining were installed on non-industrial private land-holdings.

All stands were sampled using the same method. Field crews were instructed to pace into the timber stand 100-meters and survey the area to ensure there were no roads within 100-meters, no openings in the stand, and that the stand continued in the direction of the cruise at least another 400-meters. Once the general area was surveyed, a 4-plot by 4-plot, termed the "16-plot cluster", cruise was installed with each plot 30-meters (98.4 feet) apart. On each plot, using a 10-factor prism for the mature stands, and a 1/50th acre fixed radius plot for the premerchantable stands, pine and hardwood trees were tallied, and aspect, slope, dominant understory species, and understory cover in quartiles were recorded. On each odd-numbered plot, the diameter at breast height (DBH) and the height of a dominant or codominant pine tree was recorded. On every fourth plot, the DBH for every tree tallied and the DBH and height of a low to mid-storey tree was recorded (figure 5.3). The location of the 4 corner plots were GPS'd using Trimble's GeoExplorer III (Trimble). A minimum of 150 "hits" were recorded at each GPS point.

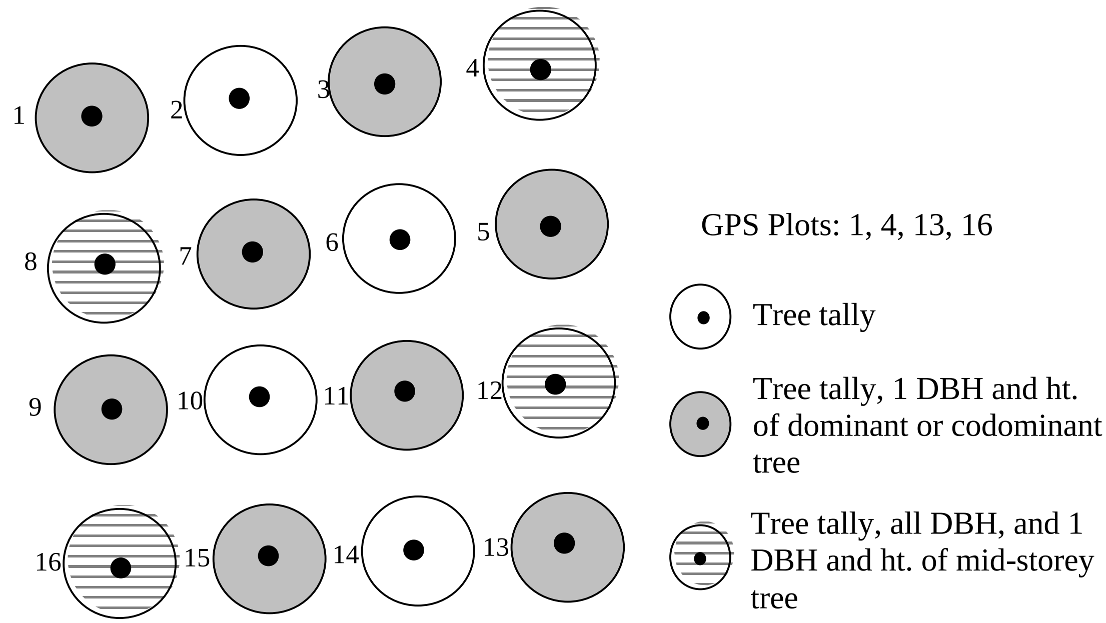

Figure 5.3 The 16-Plot Cluster

VI. METHODS

A. Remotely Sensed Variable Generation

With 6 winter (TM1w - TM5w and TM7w) and 6 summer (TM1s - TM5s and TM7s) spectral LTM bands, the number of possible variables (individual bands, ratios, products, quadratics, etc.) to enter into a regression model are numerous. For each season, there are 15 possible 2-variable products ((6!/(2!*4!)), and 30 possible 2-variable ratios (6!/4!) - 90 possible summer and winter product or ratio variables, and infinite possibilities of other combinations.

To trim the number of possible predictor variables, I established several guidelines which had to be met before being considered for analysis. First, I did not consider any cross-season variables. The summer and winter LTM images were captured approximately 6 months apart (November 1997 and May 1998). In that time, existing stands could be removed and new stands could be established resulting in a season-induced anomaly. The second criterion I established required that variables created by combining 2 different bands must be interpretable. For instance, if the ratio of bands 1 and 2 result in a value of 0.5, it would be interpreted that, for this pixel, band 2 is twice the value of band 1. Products, on the other hand, can not be interpreted in this manner. A product of 3 could be created by multiplying 2 pixels with a value of 1 and 3 or 3 and 1, each representing 2 different situations. For this reason, I only considered exponential variables created from individual bands (eg. TM1 * TM1).

Adhering to the above criteria, the following variables were considered in the analysis:

1) all individual bands (excluding the thermal band, TM6)

2) the quadradic form of each individual band,

3) all possible within season ratios, including the SR (equation 4.1),

4) the summer and winter NDVI (Equation 4.2), and

5) the modified summer and winter NDVI (NDVIp, equation 6.1).

$$NDVIp = NDVI * [1 - ((LTM5 - LTM5min) / (LTM5max - LTM5min))] \quad [6.1]$$

where,
LTM5max = the maximum LTM band 5 value in pine stands, and
LTM5min = the minimum LTM band 5 value in pine stands.

B. Data Processing

Pine basal area and volume were calculated for each plot. Pine basal area for mature stands was calculated using equation 6.2.

$$PBAplot: \ Plot\ Tally\ pine * BAF \quad [6.2]$$

Equation 6.3 was used to calculate pine basal area for the premerchantable pine stands.

$$\text{PBAplot: Plot Tally pine * (50)} \quad [6.3]$$

Mature pine basal area ranged from 0 to 290 ft^2 with a mean of 97 ft^2 and a standard deviation of 48 ft^2.

Individual regression analyses were used to predict tree heights for each 16-plot cluster. The natural log of height was regressed on the inverse of DBH using the form shown in equation 6.4.

$$lnHeight = a + b(1/dbh) \qquad [6.4]$$

Where:
lnHeight = the natural log of height
a and b = regression coefficients for a 16-plot cluster
dbh = diameter at breast height

An equation published by Borders and Harrison (1996; equation 6.5, Table 6.1) was used to predict the planted pine volume (ft^3) on the 4 "fourth" plots in each 16-plot cluster that had DBH measures of all tallied trees.

$$Y = B0*(DBH^{B1})*(Height)^{B2}-B3*(d^{B4}/DBH^{B4-2})*(Height-4.5) \qquad [6.5]$$

where:
Y = volume (ft^3) of a loblolly pine to a top diameter limit of d inches (ob)
DBH = diameter at breast height
Height = total height
d = merchantable top diameter limit outside bark (ob) in inches. A top diameter of zero was used for this value in our analysis to include total tree volume

Table 6.1 Pine volume coefficients used in equation 6.5

Variable	Coefficient
B0	0.00401246
B1	1.829011
B2	0.969142
B3	0.00249374
B4	3.684725

Natural pine volume (ft^3) was calculated using an equation published by Clark and Saucier (1990, equation 6.6, Table 6.2) for the Piedmont.

$$Y=B0(D^2)^{B1}*H^{B2}*exp(B3*d^{B4}*DBH^{B5}) \tag{6.6}$$

where:
Y = volume (ft^3) of trees to a top diameter limit of d inches (ob)
DBH = diameter at breast height
H = total height, and
d = merchantable top diameter limit outside bark (ob) in inches. Zero was used for this value in our analysis to account for total tree volume

Table 6.2 Natural pine coefficients used in equation 6.6

Variable	Coefficient
B0	0.00195
B1	1.00449
B2	1.02075
B3	-3.0643
B4	4.65458
B5	-4.95963

Using the DBH and height measures recorded or estimated for the 4 "fourth" plots in the 16-plot cluster, an average ratio relating the total pine volume to basal area, the VBAR (Shiver 1996), was established. The average VBAR was then multiplied by the basal area of the 12 remaining plots of the cluster to predict the total pine volume per acre represented by each individual plot. Mature pine volume ranged from 0 ft^3 to 6431 ft^3 with a mean of 1960 ft^3 and a standard deviation of 1338 ft^3.

Field crews recorded GPS point data at the 4 corners of each 16-plot cluster (figure 6.3) by averaging a minimum of 150 "hits". The data was then differentially corrected in Trimble's Pathfinder Office v. 2.5 (Trimble). Positional precision of differentially corrected GPS'd data was generally better than 40 feet (Cofffee & Whiffen, 2001). The data were then exported to ArcView 3.2 (ESRI) for the remainder of the spatial data processing.

Using the GPS'd corners of the 16-plot cluster, I used a customized script written in Avenue (ESRI) to insert the internal 12 cruise points. Plot-level data, including stand identification, tally, and estimated stand basal area (ft^2) and volume (ft^3) fields were then attached to their associated points using common fields recorded in both the GPS and cruise data. I will refer to the cruise points with all plot information attached as the "base data".

I processed the base data twice. In the first run, the base data were buffered by 10-meters, overlain on the LTM data, and visually inspected to see if any fell within a non-timber structure like a power line, road, harvested stand, or a cloud or cloud shadow. If the buffer did overlay an anomaly, it was eliminated form the study. I selected the 10-meter buffer because it is close to the limiting distance of the average 6.5 inch DBH tree. Of the 908 ten-meter buffers, 224 were eliminated from the study. A majority of those eliminated were collected outside the LTM image area. The rest were either in harvested areas or fell within a utility or road right-of-way.

Three-hundred and fifty-nine of the remaining plots were in mature pine stands. The mature pine buffers were once again overlain on the LTM data and the average pixel value of each LTM band and LTM-derivative within the buffer, referred to as the "zonal attributes", were calculated (Appendix B). Two-hundred and forty-six plots were randomly marked for use in the model development, and the remaining 113 plots were used to test the developed models.

In the second run, I grouped four cruise points in each quadrant (upper-left, upper-right, lower-left, lower-right) to create a new average point calculated using equation 6.7.

$$newX = (X1 + X2 + X3 + X4) / 4 \qquad [6.7]$$
$$newY = (Y1 + Y2 + Y3 + Y4) / 4$$
$$newPOINT = (newX, newY)$$

where,
X1, X2, X3, and X4 = the X GPS coordinates
Y1, Y2, Y3, and Y4 = the Y GPS coordinates

This new point dataset will be referred to as the "quadrant data". Stand metric information for the quadrant data points were averaged and attached to the newly established points. They were then buffered by 28-meters, inspected for non-timber anomalies, and the zonal attributes calculated. The 28-meter buffer was selected because it enclosed the most of the area covered by the buffers of the four points that were combined. Sixty-three out of 227 total 28-meter buffers were eliminated, again, mostly due to the fact they were collected outside of the LTM image area. Thirty-nine of the 28-meter buffers were edited, mostly due to the effects of adjacent utility and road right-of-ways. Seventy-six of the 120 plots in mature pine areas were used in the model development phase, and the remaining 44 were used to verify the models.

VII. MODEL DEVELOPMENT AND RESULTS

To gain an idea of which LTM-derived variables have the strongest linear relationship with the stand parameters of interest, I calculated the correlation coefficients for the "10-meter" and "28-meter" buffer datasets. At the 10-meter buffer level, winter LTM bands 1-3, 5 and 7 were all negatively correlated with basal area, while LTM band 4 produced a positive correlation. All single summer LTM bands were negatively correlated with basal area. These findings correspond with results from previous research conducted by Brockhaus (1992) and Batemans Bay (Coops 1998). Landsat Thematic Mapper band 5 from both the winter and summer yielded the highest single band correlation with basal area, -0.56 and -0.44, respectively. The ratio of winter LTM bands 4 and 5 yielded the highest two-band ratio correlation (0.60), and the $NDVIp\_w^2$ index resulted in the next highest correlation at 0.59. Generally, the winter ratios had a higher correlation with basal area than did the summer ratios.

There was a negative correlation with mature coniferous timber volume (ft^3) and all single LTM bands. These were the same findings obtained by Brockhaus *et. al.* (1992). As with basal area, winter LTM band 5 had the highest single band correlation, -0.53, with volume (ft^3). Landsat Thematic Mapper band 2 yielded the highest correlation (-0.53) between the summer scene and volume (ft^3). Overall, the ratio between winter bands 5 and 4 had the highest correlation with timber volume (ft^3) at -0.58.

The 28-meter buffer dataset yielded, on average, much higher correlations between the LTM-derived variables and pine basal area than did the 10-meter dataset. All single winter bands and summer bands 2-5 and 7 were negatively correlated with basal area. Both winter and summer bands 5 yielded the highest single band correlations, -0.76 and -0.81, respectively. Winter and summer bands 7 yielded high correlations as well. The ratio of summer bands 5 and 3 and NDVIp_s^2 yielded the highest correlation between basal area and LTM-derived variables with values of -0.85 and 0.84, respectively.

At the 28-meter buffer level, winter bands 1-3, 5 and 7, and all summer bands had a negative correlation with mature pine volume (ft^3). Winter band 4 had a negative correlation. Winter and summer bands 5 both yielded the highest single band correlations with -0.70 and -0.78, respectively. The NDVIp_s variable yielded the highest correlation (-0.75) between a ratio and volume (ft^3).

The LTM band 5 variable from winter and summer seems to be the most important of all bands. They had the highest single-band correlations, and were incorporated into the over all highest correlations with basal area and volume at both the 10-meter and 28-meter buffer levels. The LTM band 5 effect is also realized when comparing the NDVIs and NDVIp_s variables. At the 28-meter buffer level, the summer LTM band 5 correction factor dramatically increases the correlation between NDVIp_s and both basal area and volume (ft^3). Basal area correlation increased from -0.08 to .77, and from -0.01 to 0.75 when related to volume (ft^3). This increase was realized in the winter NDVIp variables as well.

Overall, the 28-meter buffer dataset had a stronger correlation with the forest stand parameters of interest than did the 10-meter buffer dataset. The highest LTM - basal area correlation from the 28-meter dataset was 0.26 points higher than those of the 10-meter dataset - the equivalent of an increase in R^2 of 8%. The 28-meter LTM - volume (ft^3) correlation was 0.17 points higher than those of the 10-meter dataset - the equivalent of a 2.8% increase in R^2. The increased correlation is due to the fact that more LTM pixels per plot are being sampled which reduces the variation in the LTM response values. Though there are significant correlations at the 10-meter buffer level, they are weak and do not show promise of accurately predicting the stand parameters of interest. For this reason, supported by the overall superior correlations at the 28-meter buffer level, further research will be conducted with only the 28-meter buffer dataset.

A. Regression Model Evaluation Criteria

Stepwise linear regression techniques were used to produce winter, summer, and combined winter and summer LTM - basal area models. While stepwise linear regression methods allow the user to evaluate many combinations quickly, the analyst must be mindful of the caveats associated with using this method. There are no guarantees that the models produced will be of any biological significance. One should evaluate and select the "best" model that is consistent with the fundamental underlying principles of the relationship between the dependent and independent variables. Secondly, the presence of many independent variables in the model tend to lead to multicollinearity among the variables.

I evaluated numerous models relating mature pine basal area and volume (ft3) based on their scatter plots, adjusted R^2 [7.1], and root mean squared error (RMSE) [7.2].

[7.1]

$$Adjusted\ R^2 = 1 - (((n -1) / (n - (p + 1)) * (1 - R^2))$$

where,
n = # of samples
p = # variables in the model
R^2 = coefficient of determination

[7.2]

$$RMSE = sqrt((sum ((y - yHat)**2)) / (n - (p + 1)))$$

where,
y = the ground-measured variable of interest
yHat = the LTM-predicted variable of interest
n = the number of samples
p = the number of variables in the model

Scatter plots of observed versus predicted variables were prepared to evaluate their slopes and intercepts where the linear relationships were straight with a 45 degree angle. Residual scatter plots, regression model residuals versus predicted variables, lend insight into how well the model fits the data and if there are any independent variable-related problems. The scatter in these plots should be randomly distributed about the X-axis. Patterns in the residual plot may be indicative of heteroscedasticity in the model. The adjusted R^2 is a measure of explained variation after adjusting for the number of variables used in the model (SAS 1993). RMSE is the square-root of the MSE and is considered a measure of the expected error of the estimator (Stark 2002). Once a suitable model was produced, the regression coefficients were applied to the 46 samples in the validation dataset. Those results were evaluated using the scatter plots, adjusted R^2, RMSE, relative mean absolute error (RMAE) [7.3], and relative percent error (RPE) [7.4].

$$RMAE = (sum(abs(residual/observed)))/n * 100 \tag{7.3}$$

$$RPE = sqrt((sum(residual/observed)^2)/(n - 1)) * 100 \tag{7.4}$$

RMAE is a measure of the average, absolute error of the predictor in percent terms. It was interpreted as the percent error in prediction expected when the model is applied to the dataset. RPE is a measure of the relative difference between the observed and predicted values. It is a measure of and was interpreted as how far off, plus or minus, one should expect the predicted values to be from the measured values.

B. Basal Area

The best winter (BAw, equation 7.5, Table 7.1), summer (BAs, equation 7.6, Table 7.2), and combined winter and summer (BAws, equation 7.7, Table 7.3) basal area models are listed below:

$$BAw = a + (NDVIp\_w^2 * b) \tag{7.5}$$

Table 7.1 Winter pine basal area coefficients used in equation 7.5

Variable	Coefficient
a	56.03539
b	511.21859

$$BAs = a + (NDVIp\_s^2 * b) + (TM4s/TM5s * c) + (TM5s/TM3s * d) \tag{7.6}$$

Table 7.2 Summer pine basal area coefficients used in equation 7.6

Variable	Coefficient
a	323.68143
b	379.44637
c	-58.43788
d	-85.70083

$$BAws = a + (NDVIp\_w^2 * b) + (TM5s/TM3s * c). \qquad [7.7]$$

Table 7.3 Combined pine basal area coefficients used in equation 7.7

Variable	Coefficient
a	230.50426
b	251.98906
c	-76.30904

All variables in each model are significant at a 0.05 probability level. The above models were applied to the validation dataset and compared using the previously mentioned regression model evaluation criteria.

On average, BAs and BAws both predicted basal area within plus or minus 19% of the ground-measured basal area, and one should expect to predict, on average, within 16% of the actual basal area using these equations in repeated samples (table 7.4).

Table 7.4 LTM-derived basal area model statistics

Model	Adjusted R^2	RMSE	RMAE	RPE
BAw	58.23%	21.30	16.17%	22.19%
BAs	76.70%	20.86	15.51%	18.59%
BAws	74.62%	19.72	15.23%	18.98%

The randomness and independence of the error terms can be evaluated from the residual scatter plots (figures 7.1, 7.2, 7.3).

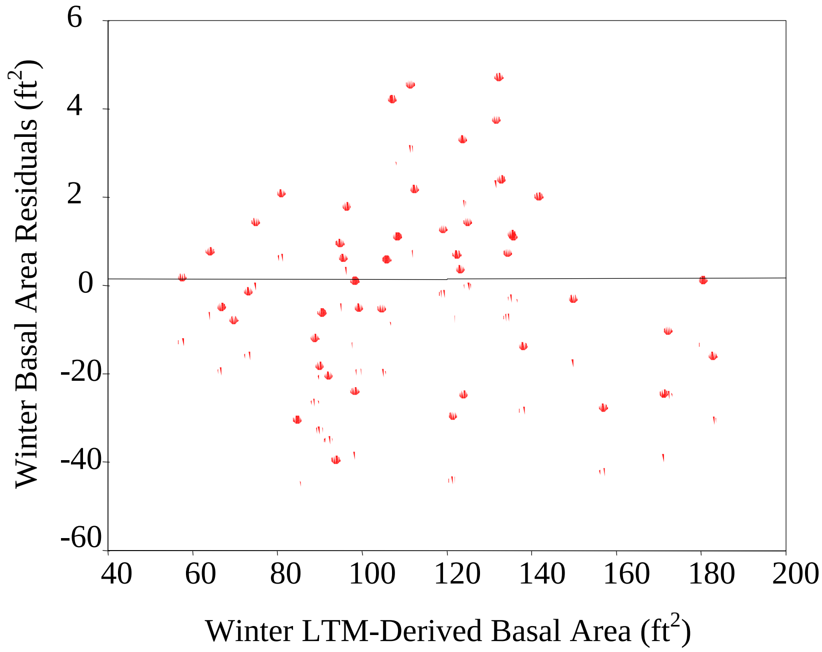

Figure 7.1 Model BAw Residual Plot

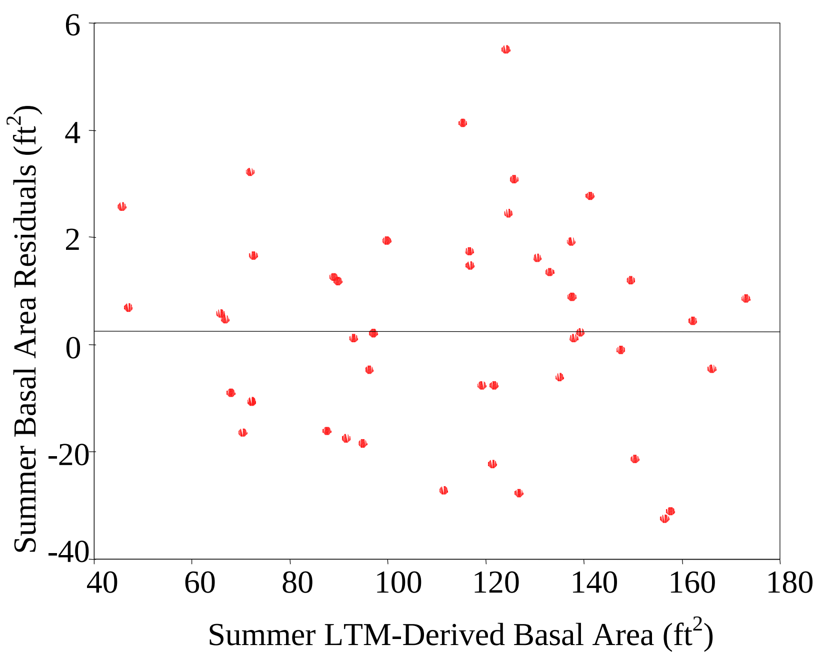

Figure 7.2 Model BAs Residual Plot

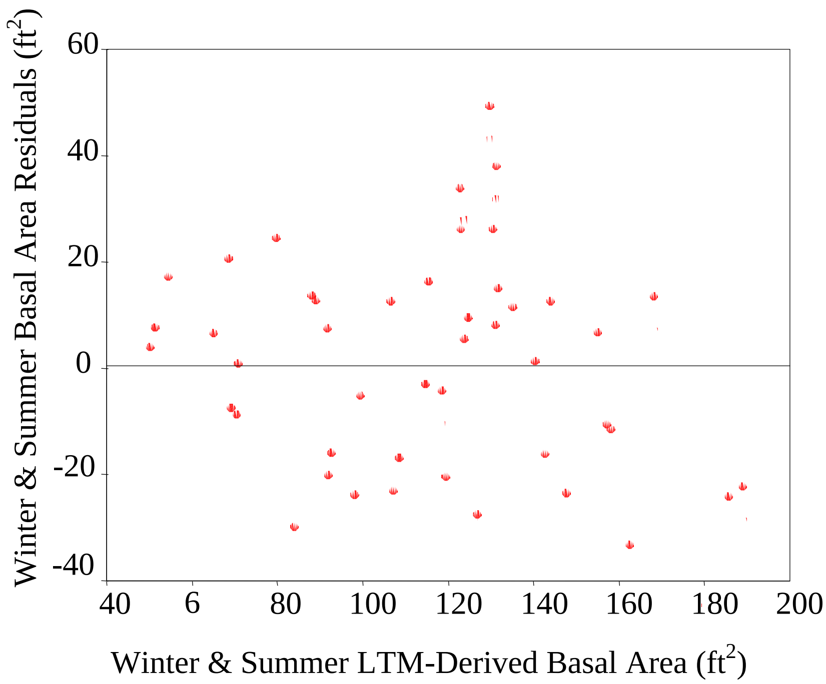

Figure 8.3 Model BAws Residual Plot

The residuals from the BAs and BAws models appear to be randomly located around the X-axis, though it appears as if the error terms from the BAw model may be correlated with the criteria variable. For this reason, and its relatively low adjusted R^2 value, the BAw model was discarded.

Two variables stood out as important factors in LTM - basal area estimation - TM5 and TM3. These two variables are incorporated into each model in one form or another. These findings are similar to others who found a high correlation between TM5 and vegetation density (Horler 1986), TM3 and TM4 and wood volume (Trotter 1997) and TM5 and basal area (Brockhaus 1992). In a study in southeastern Georgia (Landreth 2002), TM5 and TM3 were determined important factors in estimating basal area at the stand level.

These results are comparable to those found in a similar study in southeastern Georgia (Phelps 2001). Using the same methods, a strong relationship between basal area and LTM was modeled (R^2 = 71.88, RMSE = 17.23 ft^2). In a study in North Carolina, Brockhaus found a significant correlation between TM5 and basal area, but did not model the relationship due to the relatively weak relationship (R^2 = 23.00%).

C. Volume

Similar to the basal area modeling routine, I assessed many LTM - volume models for predictive ability. Volume was modeled as a function of the variables contained in the LTM - basal area models in addition to other LTM-derived variables that demonstrated high correlation with volume. Three models are presented to demonstrate the relationship between LTM data and coniferous volume. Building on the BAs model (equation 7.6), volume was evaluated as a function of those variables

($NDVIp\_s^2$, TM4s/TM5s, and TM5s/TM3s), minus the TM4s/TM5s ratio which was insignificant in the model at an alpha level of 0.05. VOLbas (equation 7.8) has the following form:

$$VOLbas\ (ft^3) = a + (TM5s/TM3s * b) + (NDVIp\_s^2 * c). \quad [7.8]$$

Table 7.5 Model 1 coefficients used in equation 7.8

Variable	Coefficient
a	5648.0387
b	-1905.87374
c	7868.34854

The second model (VOLoth, equation 7.9, Table 7.6) included variables contained in each basal area model and other highly correlated LTM-derived variables.

$$VOLoth\ (ft^3) = a + (TM5s/TM3s * b) + (NDVIp\_w^2 * c) + (TM2s * d) + (TM5w/TM4w * e) + (TM2s/TM4s * f) \quad [7.9]$$

Table 7.6 Model 2 coefficients used in equation 7.9

Variable	Coefficient
a	7847.76795
b	- 2260.22266
c	14038
d	- 217.75879
e	2800.27925
f	6026.92246

The third model (VOLsub, equation 7.10, Table 7.7) was a subset of model 2, initially to test the significance of the TM2s/TM4s ratio.

$$VOLsub\ (ft^3) = a + (TM5s/TM3s * b) + (NDVIp\_w^2 * c) + (TM5w/TM4w * d) \quad [7.10]$$

Table 7.7 Model 3 coefficients used in equation 7.10

Variable	Coefficient
a	3005.95526
b	-1986.11482
c	16123
d	2211.04598

Applying the VOLoth model (equation 7.9), minus the TM2s/TM4s ratio, yielded a model in which the TM2s variable was not significant. In this case, the interaction between the two variables were accounting for variation in the criteria variable, though the variables independent of the other did not. With the goal of a parsimonious model, VOLsub does not include the TM2s/TM4s and TM2 variables. All variables in each model were significant at a 0.05 probability level.

The measured versus predicted scatter plots (figures 7.4, 7.5, 7.6) reveal linear relationships with each model and volume. The poor performance of the VOLbas model, as seen in Table 7.8, suggests that variables other than the basal area indicators are needed to estimate volume.

Table 7.8 LTM-derived volume (ft^3) model statistics

Model	Adjusted R^2	RMSE	RMAE	RPE
VOLbas	59.84%	700.93	22.01%	30.54%
VOLoth	73.14%	671.98	20.11%	26.43%
VOLsub	70.14%	671.12	20.59%	27.23%

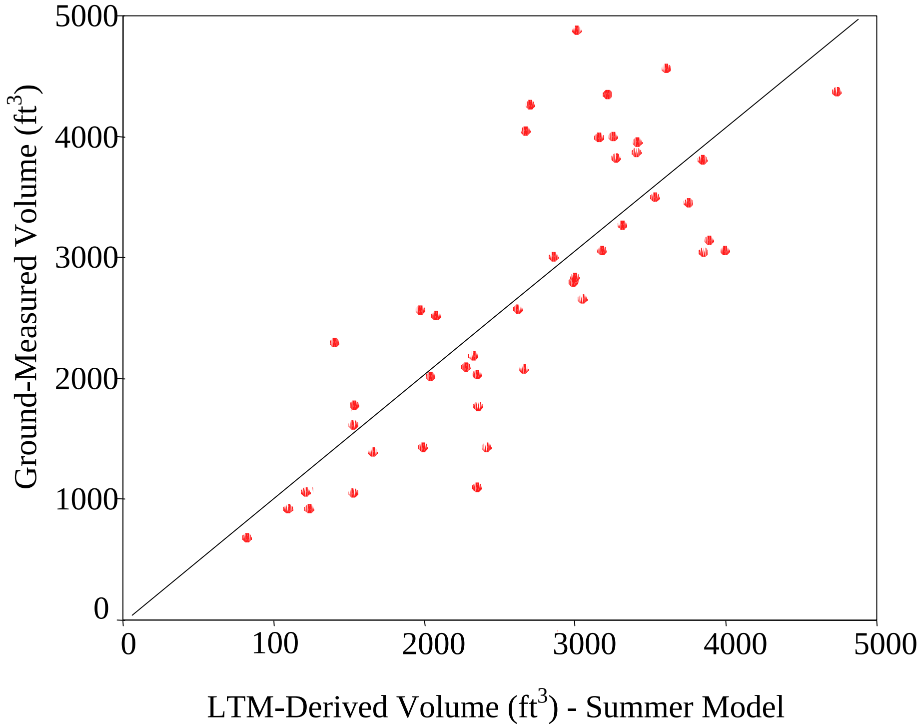

Figure 7.4 VOLbas Model: Measured Volume vs. Predicted Volume

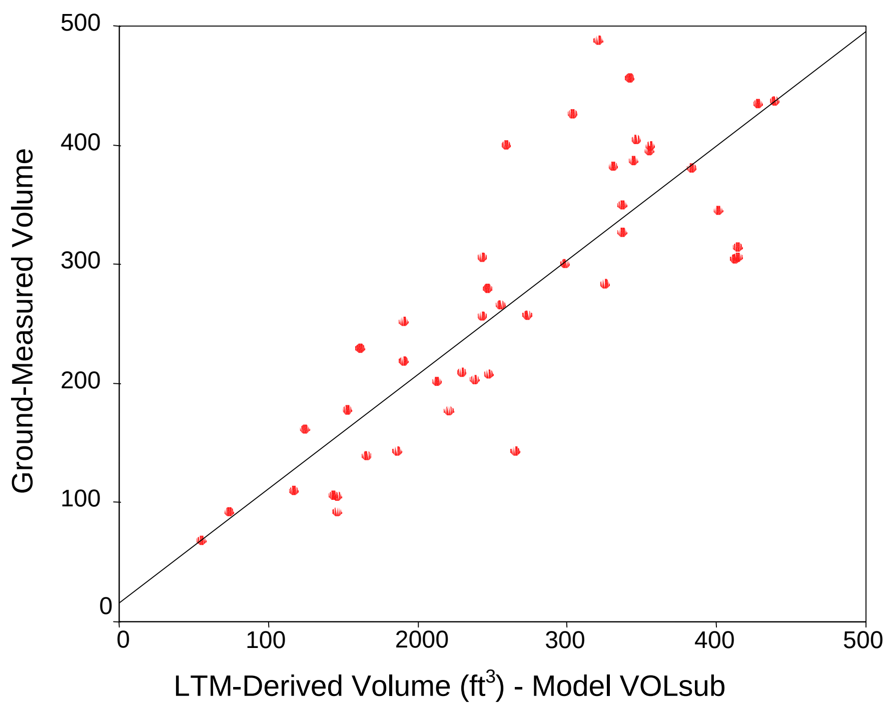

Figure 7.5 VOLoth Model: Measured Volume vs. Predicted Volume

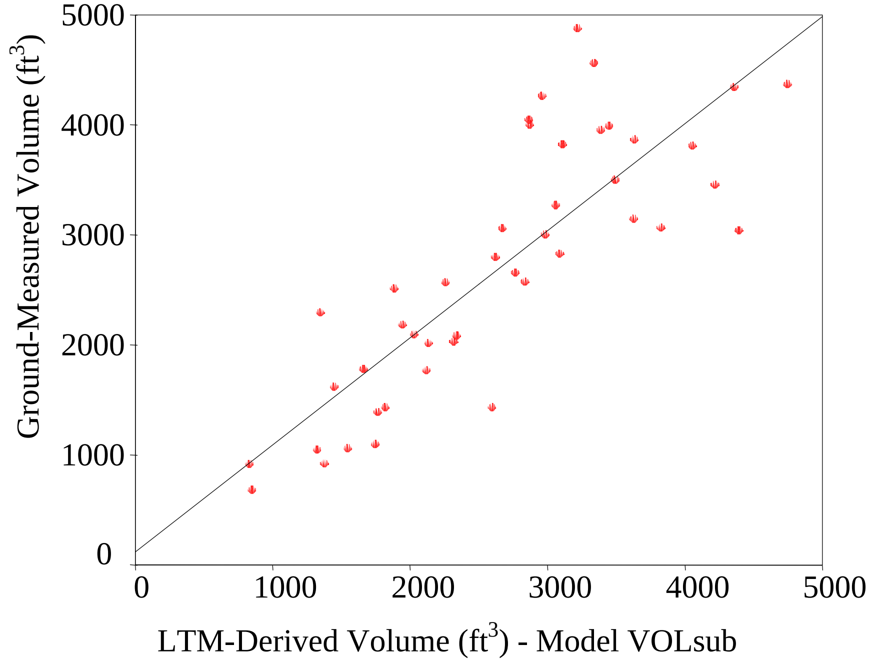

Figure 8.6 VOLsub Model: Measured Volume vs. Predicted Volume

The VOLoth and VOLsub models performed the best overall. Both estimated volume within plus or minus 28% and had similar RMSE and RMAE values (Table 7.8).

The residual plots for VOLbas and VOLsub (figures 7.7, 7.8) reveal that LTM's volume predictive ability decreases as volume increases - possible heteroscedasticity. Correlation among explanatory variables was expected. The TM5w and TM4w variables are incorporated in both models as a ratio and as $NDVIp\_w^2$. The TM2s variable was incorporated individually and as a ratio in VOLoth.

Again, TM5 and TM3 stood out as important factors in LTM - volume estimation. These findings are supported by conclusions drawn by Horler (1986), Brockhaus (1992), and Trotter (1997). A significant relationship (R^2 = 62.51%) between combinations of these variables and volume in research in southeastern Georgia (Landreth 2002) suggests that TM5 and TM3 are vital in volume estimation at the stand level.

D. Volume - Basal Area Relationship

Recognizing the method by which volume was calculated, volume as a function of basal area (VBAR, Shiver 1996), it is easy to understand why the ground-measured volume and ground-measured basal area are highly correlated (R^2 = 87.20%, RMSE = 408.37) (figure 7.9). A similar relationship exists between the ground-measured volume and LTM-derived basal area (R^2 = 70.00%, RMSE = 545.60) (figure 7.10). Figure 7.10 suggests that it may be possible to model ground-measured volume as a function of LTM-estimated basal area.

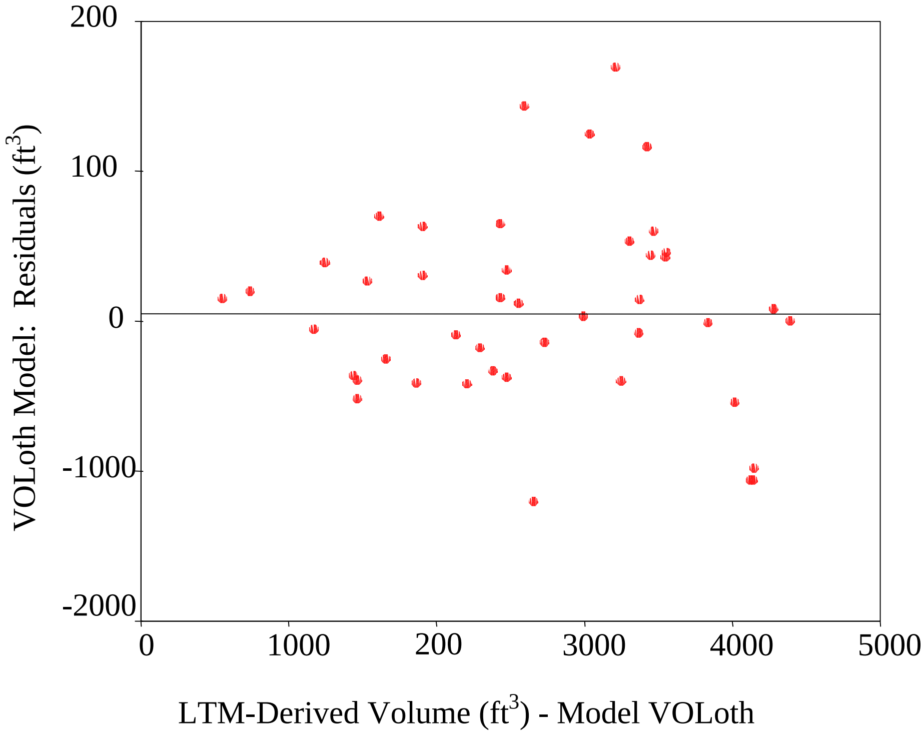

Figure 7.7 VOLoth Model Residual Plot

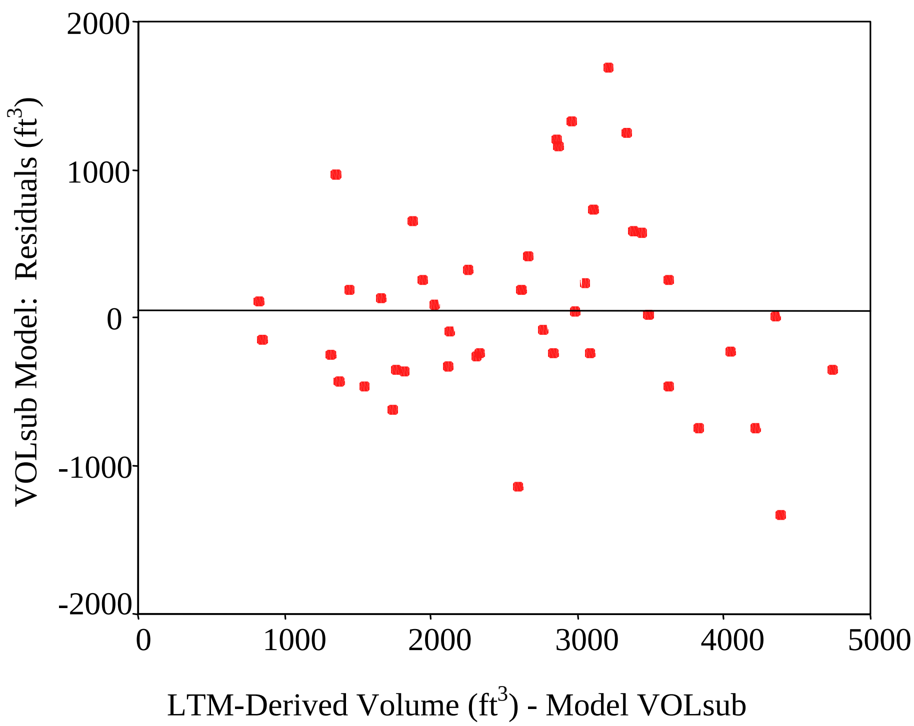

Figure 7.8 VOLsub Residual Plot

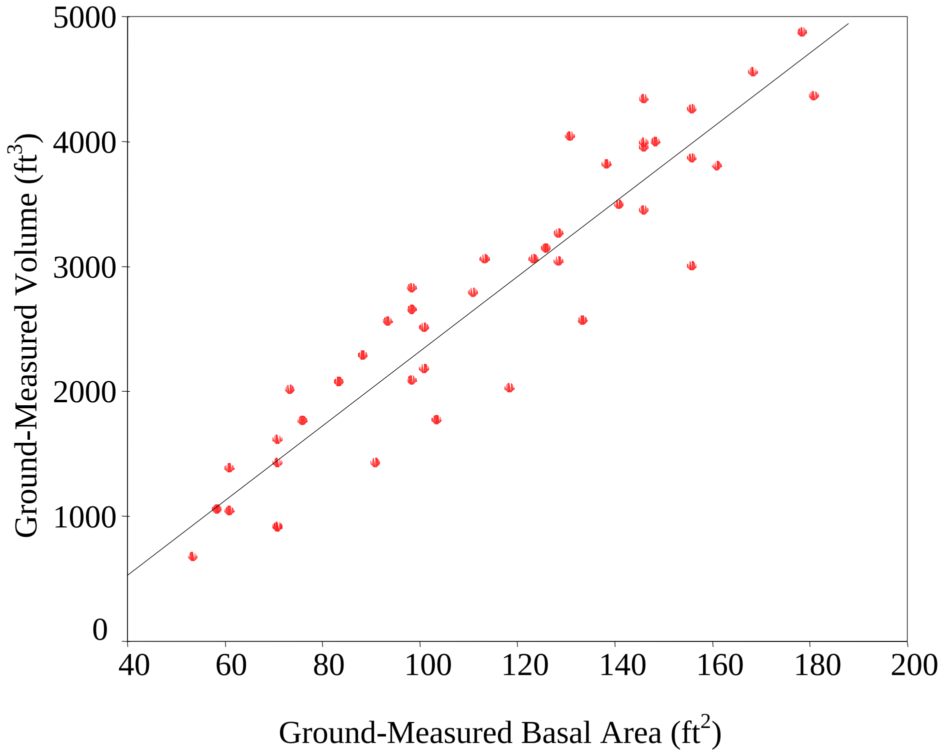

Figure 7.9 Ground-Measured Volume vs. Ground-Measured Basal Area

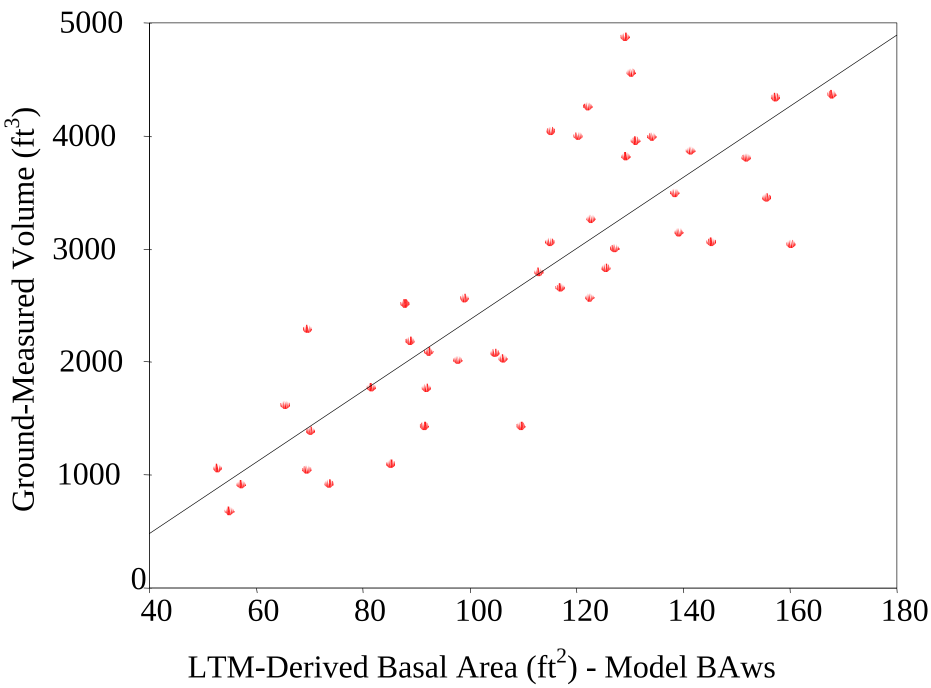

Figure 7.10 Ground-Measured Volume vs. LTM-Derived Basal Area

A seemingly unrelated regression (SUR) model may be appropriate in this case. SUR models can be implemented when a number of linear equations are used to estimate related variables (Borders 1989). A possible scenario in which this situation may arise is when one wants to estimate timber volume as a function of LTM data and basal area, where basal area is estimated as a function of LTM data as well. Hypothetical equations are listed below:

estBA = f(TM1, TM2, TM3)

estVOL = f(estBA, TM4, TM5, TM6).

If basal area is evaluated separately and then used in the volume equation, the ordinary least squares (OLS) assumption that the independent variables are known without error is violated since *estBA* appears as both an independent and dependent variable. It would be unrealisitc to expect that the errors of the *estBA* model are not correlated with the errors of the *estVOL* model. This scenario may lead to "least squares bias" in which parameter estimates will be biased and inconsistent. A biased estimator suggests that, in repeated samples, the expected value of that estimator will not equal the population parameter. An inconsistent estimator will not converge to the true population parameter as the sample size nears the total population, as does a consistent estimator. Thus, least squares bias can lead to poor parameter estimates (Borders 2001).

To explore the use of a system of equations to estimate volume as a function of LTM data and a LTM-estimated basal area, I developed the following model (equation 7.11, Table 7.9).

[7.11]

$$BAsur = a + (NDVIp\_w^2 * b) + (TM5s/TM3s * c)$$
$$VOLsur = d + (BAsur * e) + (TM5w/TM4w * f).$$

Table 7.9 SUR Model coefficients used in equation 7.8

Variable	Coefficient
a	191.3068
b	321.5357
c	-59.7595
d	-2559.2
e	37.35821
f	1372.503

The BAsur model estimated basal within plus or minus 19% of the ground-measured basal area, and when compared to the previous basal area models, had similar RMSE and RMAE values and a slightly lower R^2 value (Table 7.10).

Table 7.10 LTM-Derived SUR volume model statistics

Model	Adjusted R^2	RMSE	RMAE	RPE
BAsur	71.01%	19.99	14.92%	18.73%
VOLsur	65.15%	669.79	20.31%	26.82%

The VOLsur model performed equally well. The ground-measured volume was estimated within plus or minus 27%, and had similar RMSE and RMAE values as the previous volume models while having a slightly lower adjusted R^2 value (Table 7.3). Residual scatter plots from both models suggest that as basal area and volume increase, LTM's predictive ability decreases (figures 7.11, 7.12).

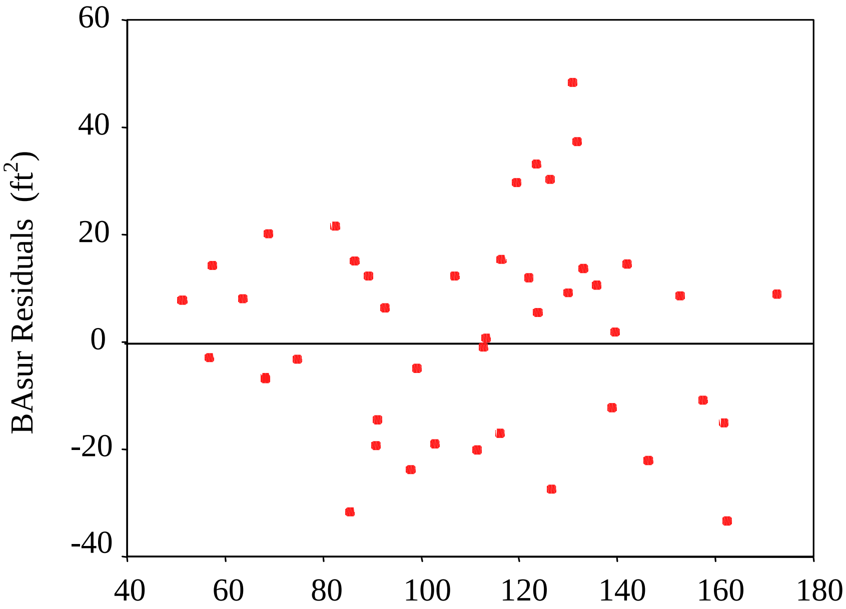

Figure 7.11 Estimated Basal Area - Model BAsur

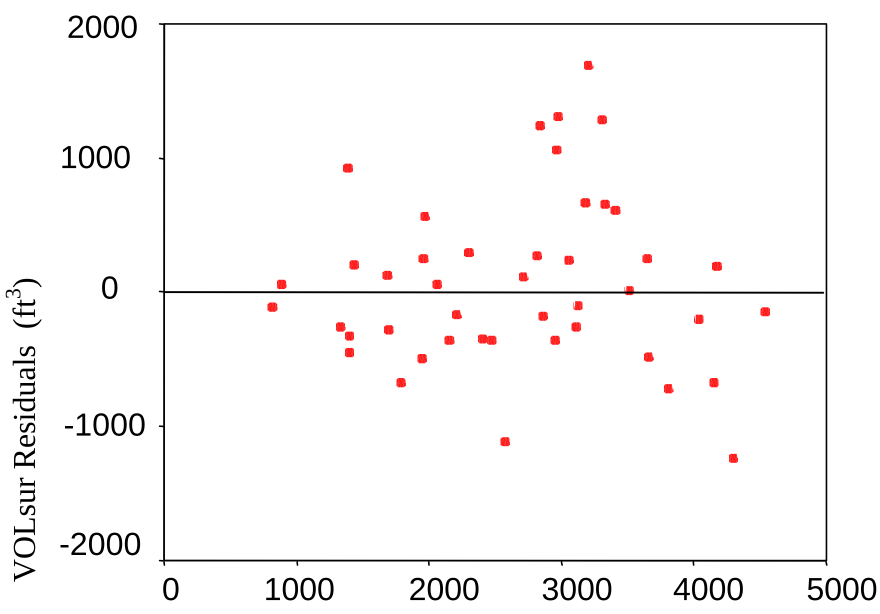

Figure 7.12 Estimated Volume - Model VOLsur

VIII. DISCUSSION AND IMPLEMENTATION

A. Basal Area

Three basal area-LTM models, one based on winter data (BAw), one based on summer data (BAs), and one based on a combination of both seasons (BAws) were assessed.

$BAw = f\,(NDVIp\_w^2)$
$BAs = f\,(NDVIp\_s^2, TM4s/TM5s, TM5s/TM3s)$
$BAws = f\,(NDVIp\_w^2, TM5s/TM3s)$

The BAw model, utilizing only the NDVIp_w2 variable, yielded a significant but relatively weak relationship (table 7.1). Both the BAs and BAws models performed equally well, predicting basal area within 19% of the ground-measured basal area. Due to the fact that only one (summer) LTM dataset is required to apply the model, reducing implementation cost, I selected the BAs model as the best overall basal area model. The BAs model predicted basal area within plus or minus 19% (RPE = 18.59%), and one should expect to predict, on average, within 16% (RMAE = 15.51%) of the ground-measured basal area in repeated samples.

Three LTM bands, in one form or another, were identified as significant variables in the LTM - basal area estimation process. The ratio of leaf moisture and density sensitive TM5s and chlorophyll-sensitive TM3s reveals an inverse relationship with basal area. Both variables reflect relatively small amounts of energy in high basal area stands due to the abundance of green leaves (that contain both water and chlorophyll). As the stand decreases in volume, and assumingly decreases in leaf mass, the amount of reflected energy increases.

The ratio of water-absorbing TM4s and TM5s produces another positive relationship with basal area. This relationship is driven by TM5s and its sensitivity to leaf moisture and density. In high basal area stands, where leaf moisture and density is high, reflectance is relatively low. As the relationship trends downward to the low basal area region, the TM5s reflectance increases due to the absence of leaves and leaf moisture. The TM4s response follows the same trend, only not as pronounced, yielding low ratio values at the low basal area regions and high values at the higher regions.

The third significant ratio was the squared-NDVIp for both winter and summer. NDVI is commonly used to monitor the presence and/or absence of green vegetation in landcover and landcover change studies (Ustin 1998). NDVI produces relatively higher values in green vegetated areas compared to those in nonvegetated areas. The range of TM5 values from coniferous-only regions are taken into consideration in the correction factor. The "TM5-pine corrected" NDVI produces positive values for coniferous regions, and (near) negative values for all others.

B. Volume

Four models were developed to evaluate LTM's volume (ft^3) predicitive ability:

VOLbas: volume (ft^3) *= f (TM5s/TM3s, NDVIp_s*^{2}*)*
VOLoth: volume (ft^3) *= f (TM5s/TM3s, NDVIp_w*^{2}*, TM2s,*
TM5w/TM4w, TM2s/TM4s)
VOLsub: volume (ft^3) *= f (TM5s/TM3s, NDVIp_w*^{2}*, TM5w/TM4w)*
VOLsur: volume (ft^3) *= f (BAsur, TM5w/TM4w),*
where
BAsur: basal area (ft^2) *= f (NDVIp_w*^{2}*, TM5s/TM3s).*

VOLbas, volume as a function of the variables in the BAs model, yielded a significant but weak relationship (table 8.1).

Table 8.1 Volume Model Comparison

Model	Adjusted R^2	RMSE	RMAE	RPE
VOLbas	59.84%	700.93	22.01%	30.54%
VOLoth	73.14%	671.98	20.11%	26.43%
VOLsub	70.14%	671.12	20.59%	27.23%
VOLsur	65.15%	669.79	20.31%	26.82%

This suggests the model was under fit and additional information, other than the basal area indicators, is required to accurately estimate pine volume. VOLoth, VOLsub, and VOLsur performed equally well, producing estimates within plus or minus 28% of the ground-measured volumes, and similar RMSEs, RMAEs (table 8.1). Since the basal area and volume models are intended for individual use, I determined that implementing the system of equations method was not required, and selected the VOLsub as the best model. By eliminating 2 variables from the VOLoth model (TM2s and TM2s/TM4s), I've removed possible sources of heteroscedasticity and produced a parsimonious model.

It is evident in the VOLsub scatter plot (figure 7.8) that as volume reaches the 3,000 to 3,500 cubic-foot mark, LTM's predictive ability decreases. Over time, most coniferous stands will increase in volume, up to, and after the point of crown closure. After crown closure, the LTM sensor is not sensitive as to the increase and then the leveling off of volume since it is most affected crown reflectance (Oladi 2001) after it reaches 100% canopy closure. The forementioned 3,000 to 3,500 cubic-feet mark most likely defines the upper most level at which volume can be accurately estimated in this dataset.

Many of the same relationships observed in the basal models are evident in the volume models. The ratio of TM5s and TM3s and both winter and summer NDVIp[2] variables contribute heavily to the LTM - volume models. Figure 8.1 shows a linear relationship between LTM-derived volume and LTM-derived basal area.

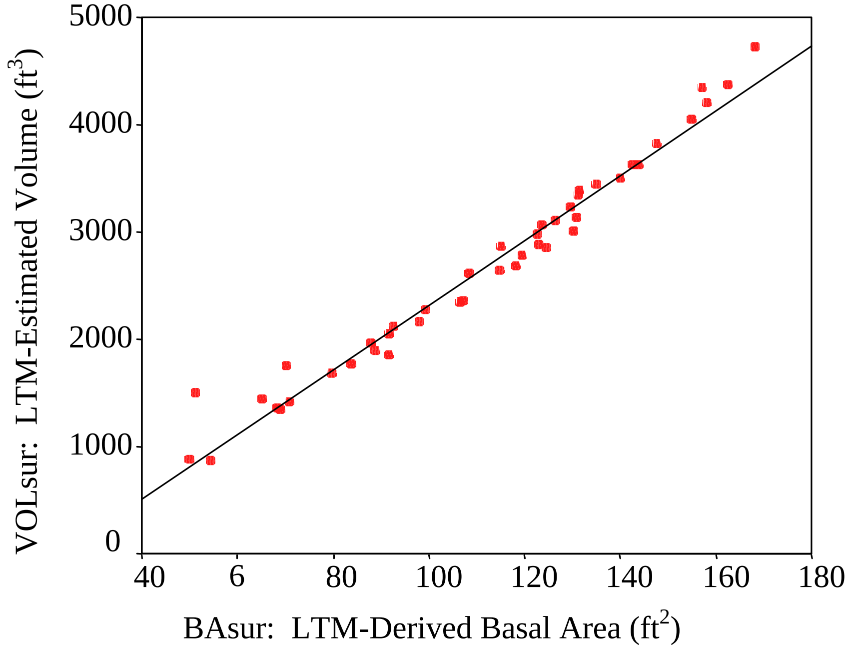

Figure 8.1 LTM vs. SURE Volume Models

It can be assumed that the LTM-derived variables contribute to the volume equations for the same reason they did in the basal area models. The TM5w - TM4w ratio contributes information relevant to leaf density, displaying an inverse relationship with coniferous volume. The TM2s variable is an indicator of vegetation vigor, again, revealing an inverse relationship with volume. The ratio of TM2s and TM4s lends insight about the rate of growth and leaf density and moisture.

C. Biological Effects On LTM - Biomass Estimation

Both TM5 and TM3 played an important role in basal area and volume estimation. This is supported by the work of Horler (1986), Brockhaus (1992), and Trotter (1997). Reflectance in the visible red band, TM3, is driven by the physical properties of the foliage being sensed. Chlorophyll absorption is high in these wavelengths, returning relatively little reflected energy back to the sensor over areas covered in green vegetation. Conversely, areas with relatively small amounts of green vegetation return more reflected energy (Turner 1999). Solar energy is strongly absorbed over vegetated areas in the shortwave near-infrared band, TM5, returning relatively small amounts of reflected energy. Driven by leaf moisture, vegetation density, and shadowing, areas with an abundance of green leaves will absorb relatively more solar energy in these wavelengths than sparsely vegetated areas (Coops 1998).

Assuming the above relationships hold true, low TM5 - TM3 ratio values can be assumed to represent the lower density stands, absent of an abundance of green vegetation. High ratio values are assumed to represent areas with a high density and a plethora of green vegetation. Figure 8.2, demonstrates the relationship between the ground-measured volume and the TM5s - TM3s ratio. The linear relationship holds true up to about 3500 to 4000 ft^3. After which, it appears as if the linear relationship weakens. At this point, several factors could be affecting the relationship. As the stand volume increases, the canopy closes, shadowing both by and within the canopy increases, resulting in decreased reflectance in TM 5 (Figure 8.3) and TM 3 (figure 8.4).

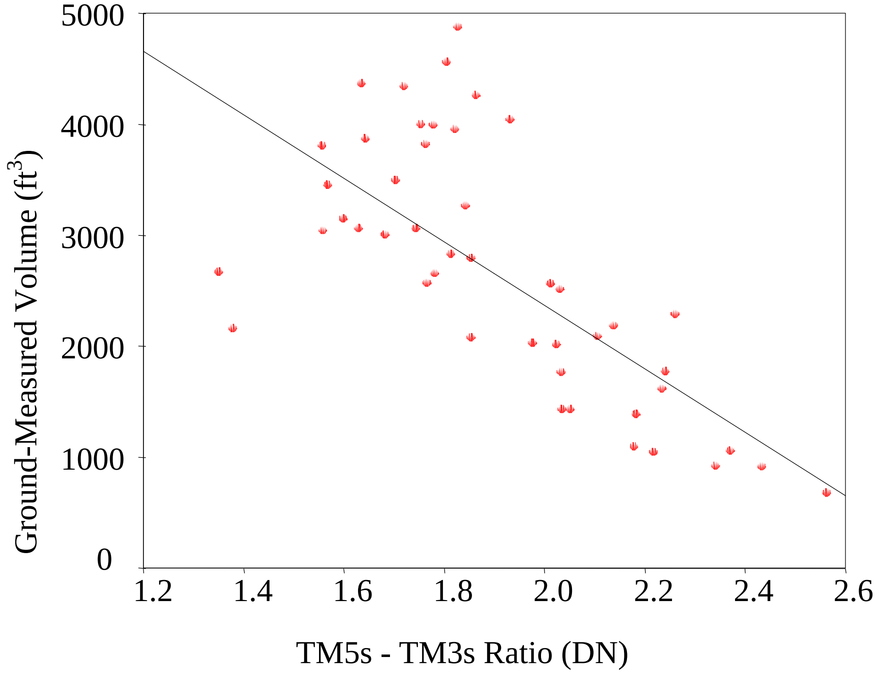

Figure 8.2 Ground-Measured Volume vs. TM5s - TM3s Ratio

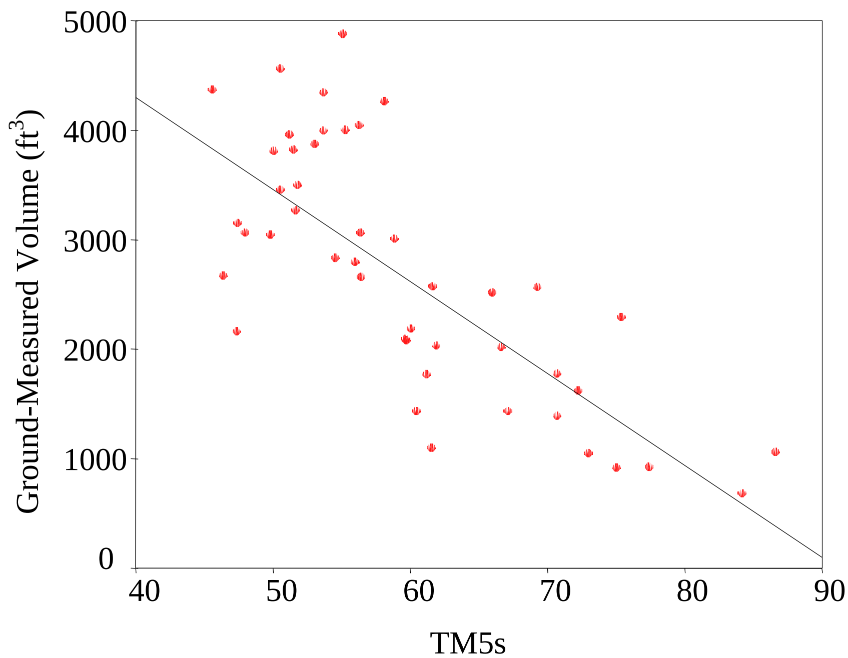

Figure 8.3 Ground-Measured Volume vs. TM5s

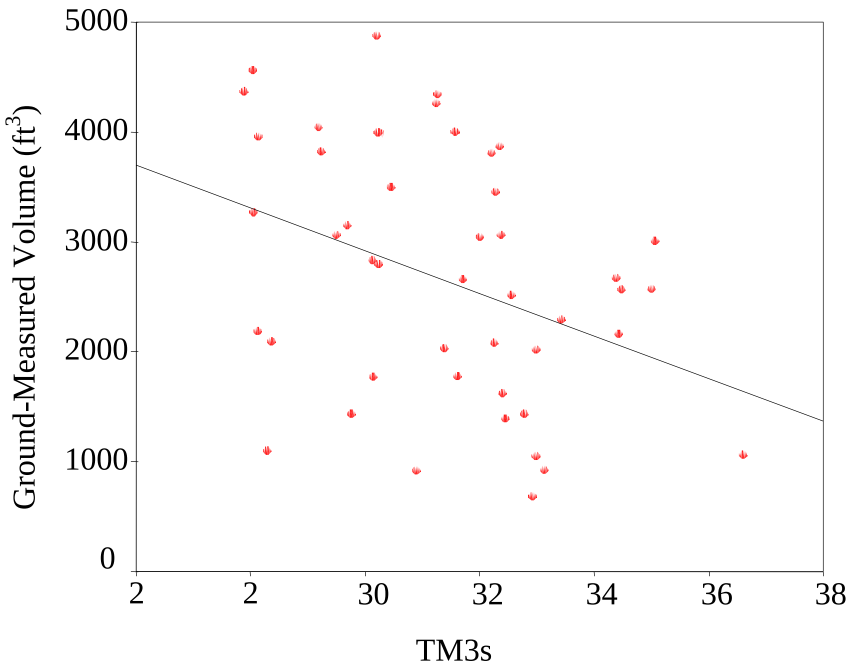

Figure 8.4 Ground-Measured Volume vs. TM3s

The LTM sensor is not as sensitive to this increase in volume since it is most affected by crown reflectance (Oladi 2001) after it reaches 100% crown closure at an earlier age. This reinforces the notion that there is an upper-most level at which volume can be accurately estimated in this dataset. This explains the appearance of decreased accuracy in estimation at higher levels of volume (figures 7.7 and 7.8).

NDVIp_w (equation 6.1) was another significant variable in the basal area and volume models. NDVI has been related to LAI (Turner 1999, De Jong 1994, Nimani 1993) which is correlated with present net primary productivity of the stand (Chen 1998). Turner (1997) and De Jong (1994) both found that areas with a low LAI have relatively high amounts of reflected energy in the RED wavelengths (TM3). As stated previously, reflectance in the RED wavelengths over green vegetated area is low due to high absorption by chlorophyll. They also found that areas with a relatively high LAI have high amounts of reflected energy in the NIR band due to the reflectance properties of lignin in plant cell walls in this portion of the spectrum. Figure 8.5 reveals the positive relationship between NDVIw and volume. This relationship is driven by the fact that high TM4 values (high reflectance over vegetated areas due to the lignin component in leaves) yield a high NDVIw, and conversely, high TM3 values (high reflectance due to the lack of green vegetation and limited chlorophyll absorption) yield a low NDVIw (figure 8.6). This relationship is pronounced when the TM5 correction factor is applied (figure 8.7).

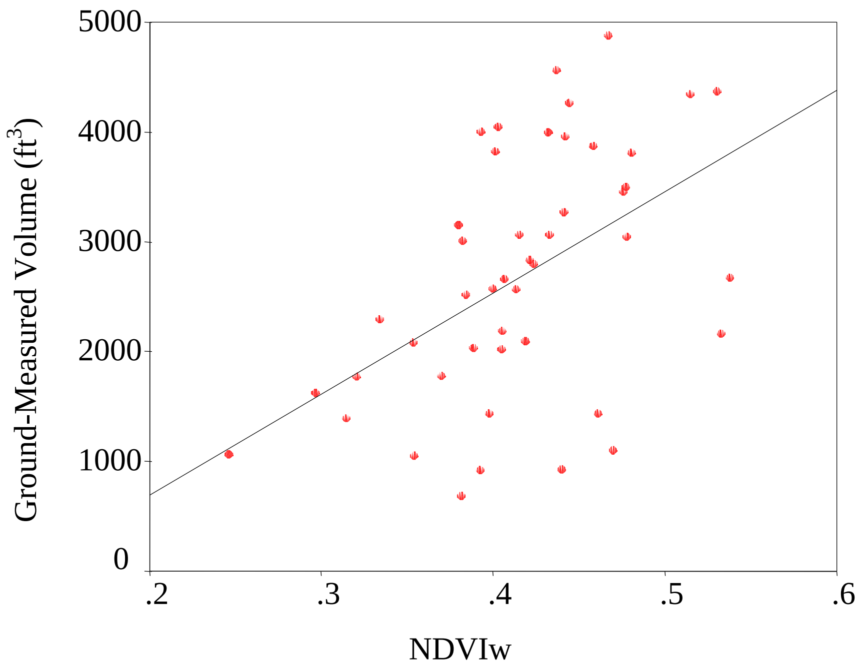

Figure 8.5 Ground-Measured Volume vs. NDVIw

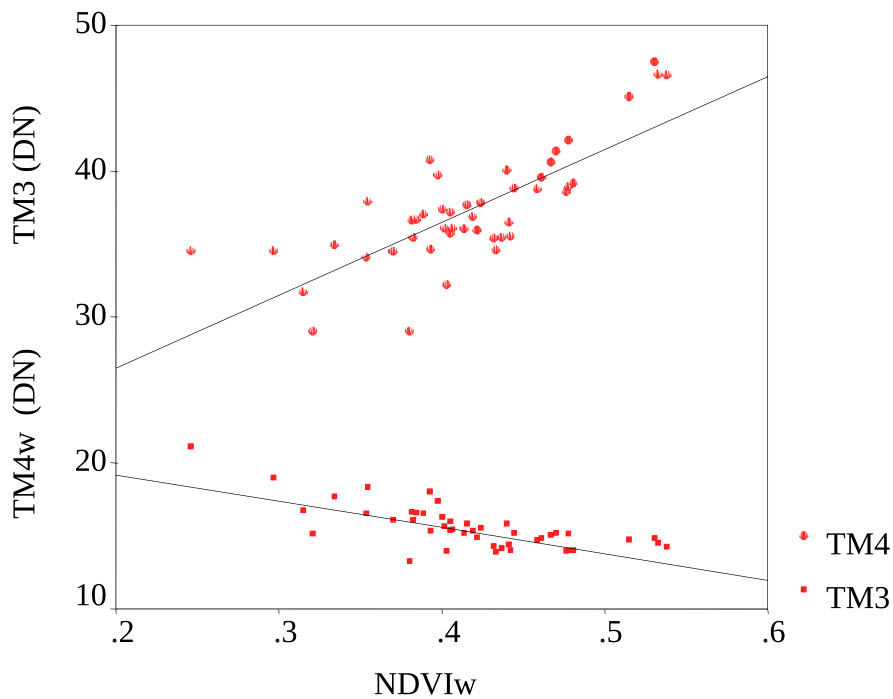

Figure 8.6 TM4w and TM3w vs. NDVIw

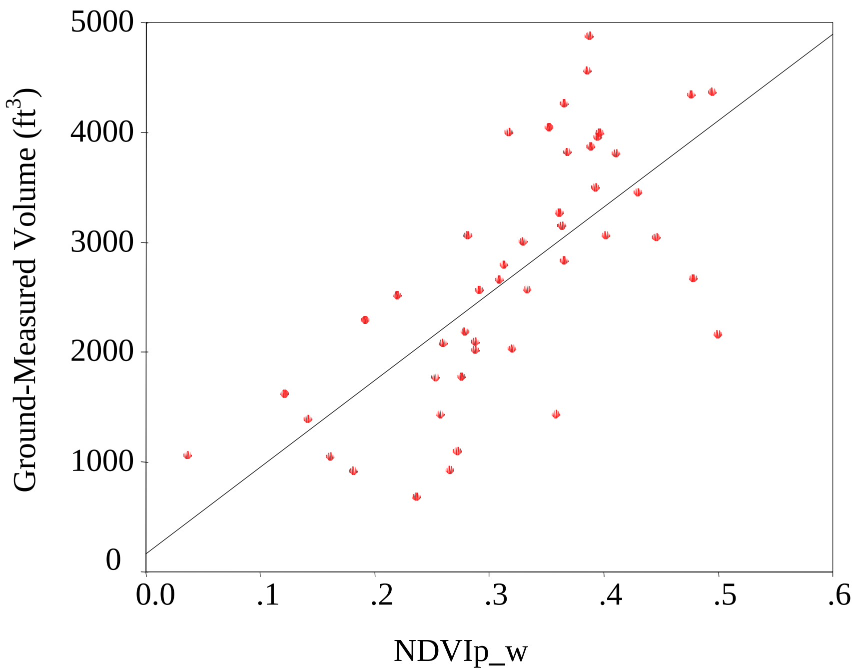

Figure 8.7 Ground-Measured Volume vs. NDVIp_w

The ratio of TM5w and TM4w is driven mainly by leaf moisture content sensed in TM4 and tree canopy density from TM5. This ratio has been used to locate areas of coniferous forest damage where high ratios characterize high damage sites, and low ratios characterize low damage sites (Zuuring 2001). This relationship occurs due to the fact that as the leaf dries out, its TM5 reflectance increases while TM4 remains relatively unaffected. This reasoning holds true in the context of the TM5w - TM4w ratio in this model as well. Areas of low volume and relatively few leaves have a lower moisture content, yielding a high ratio value (figure 8.8).

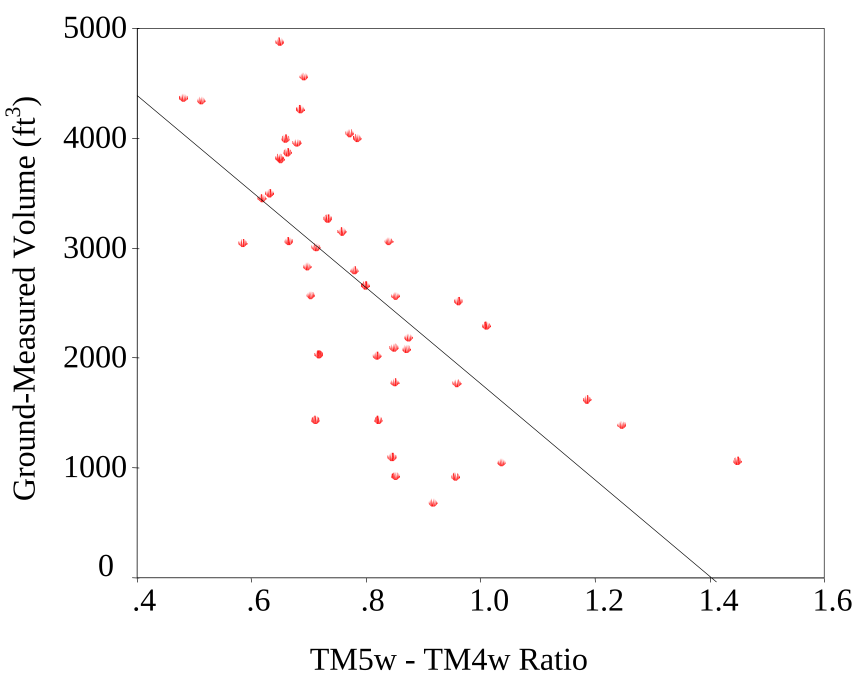

Figure 8.8 Ground-Measured Volume vs. TM5w - TM4w Ratio

The ratio of TM2s and TM4s is driven by TM2s' sensitivity to green reflectance from healthy vegetation which is used to assess vegetation vigor (figure 8.9).

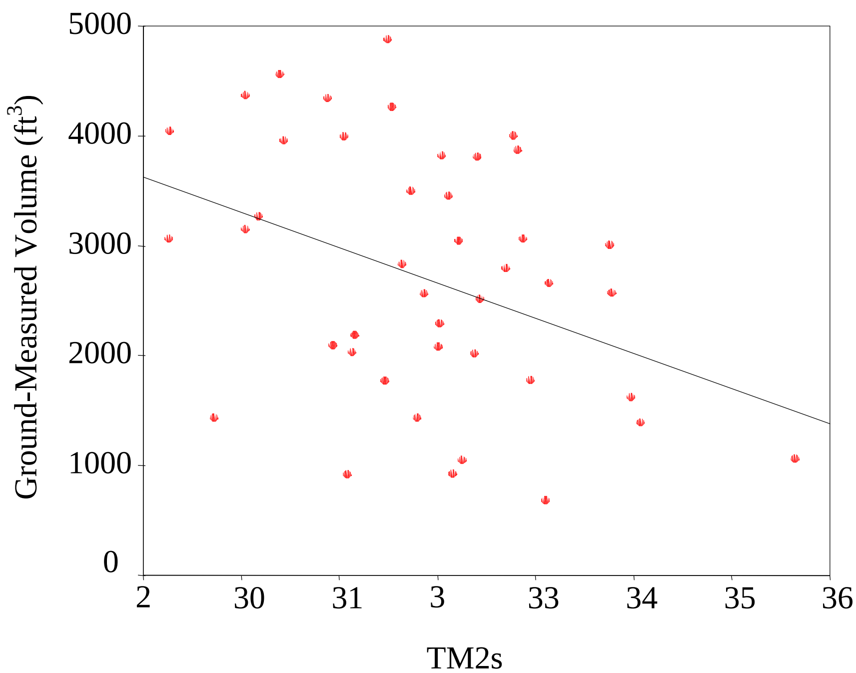

Figure 8.9 Ground-Measured Volume vs. TM2s

As volume increases over time, and assumedly, the stands vigorous growth decreases, so does reflected energy in the TM2 wavelengths.

The TM4s band is negatively correlated with volume (figure 8.10) which suggests the effects of decreasing leaf moisture and area absorption in the NIR wavelengths. A fast growing stand (high TM2s), with many leaves (high TM4s) produces a relatively low ratio value. The older, slower growing stands (low TM2s and low TM4s) produce a higher ratio (figure 8.11).

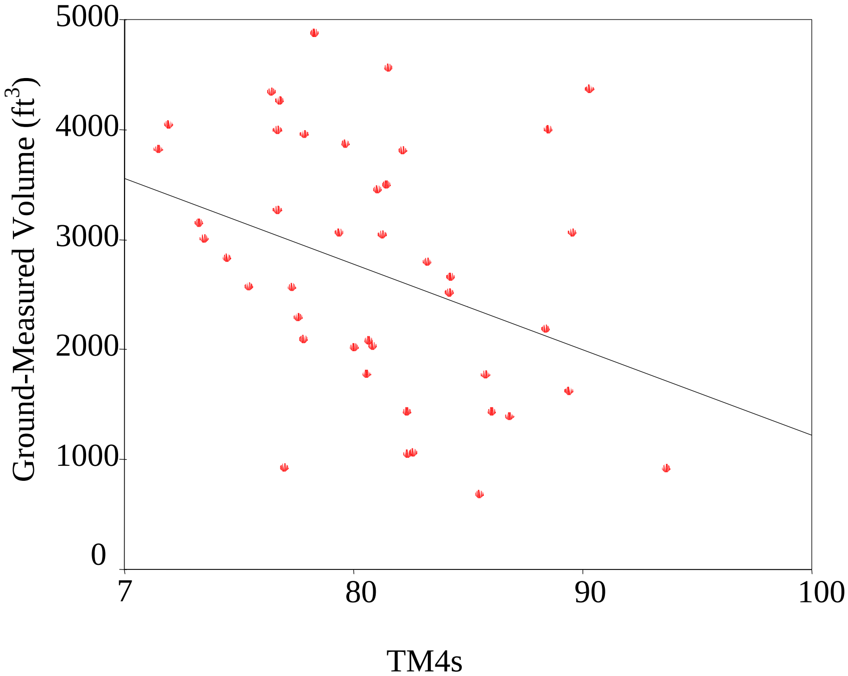

Figure 8.10 Ground-Measured Volume vs. TM4s

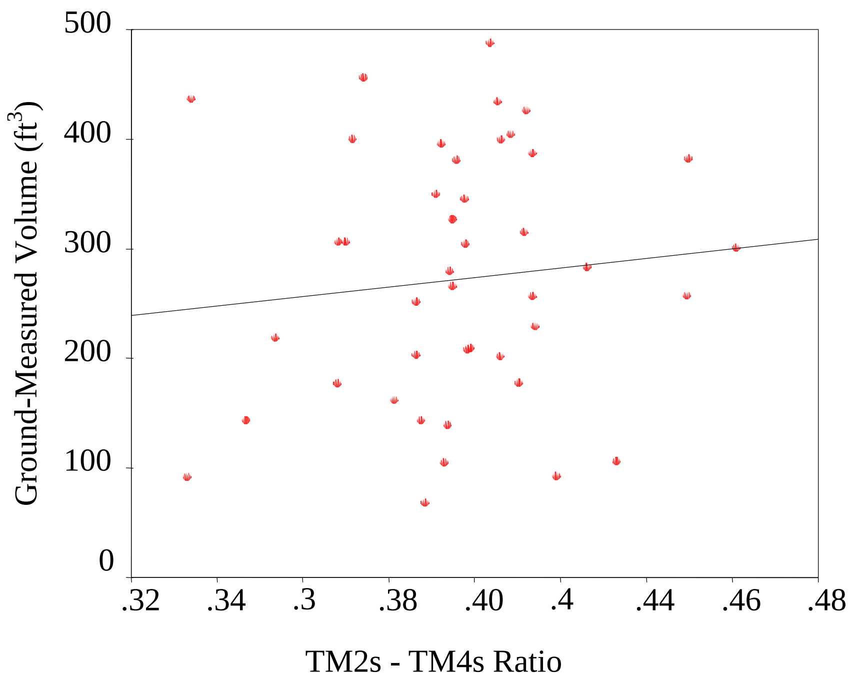

Figure 8.11 Ground-Measured Volume vs. TM2s - TM4s

D. Implementation Of LTM - Volume Estimation

The following demonstrates the processes used to apply the VOLsub model to 15 counties in the LTM scene (figure 8.12).

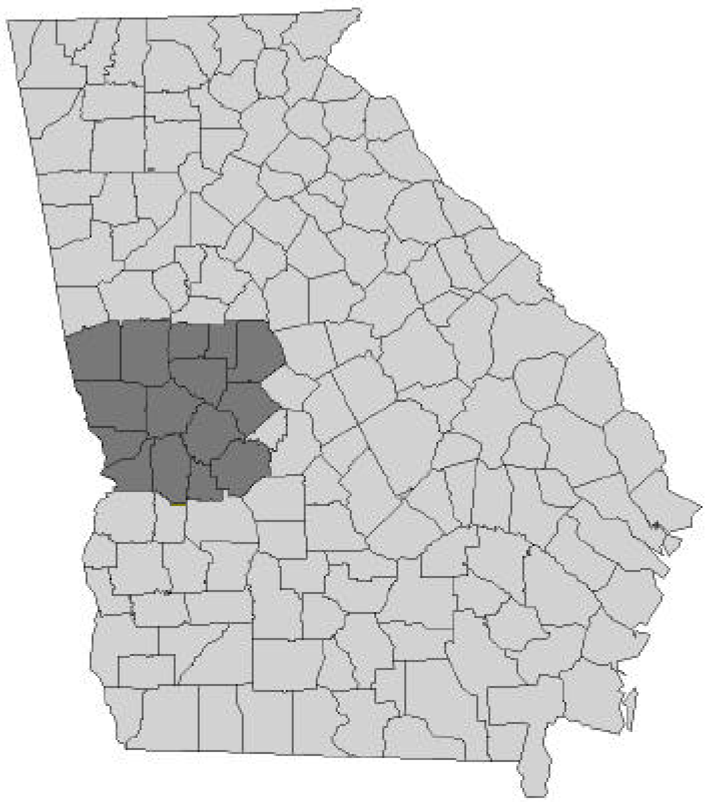

Figure 8.12 Fifteen Eastern Georgia County Application Area

Before applying the model, all non-coniferous pixels were masked. I used the NDVIp_w variable to filter the image, assuming all pixels with a value of less than 0.2 were non-coniferous. These cells were reclassified as 0. Applying the VOLsub equation to the appropriate LTM ratios in ArcView 3.2 produced an estimate of volume per acre represented by each pixel. Volume per acre was scaled down to volume per pixel using the following equation:

$$volume/pixel = \frac{(PixelValue\ vol/acre * 30m * 30m * 3.28\ ft/m * 3.28\ ft/m)}{(43560\ ft2/acre)}.$$

Total volume per pixel was calculated by multiplying the volume per pixel estimate by the number of pixels in each volume class. The Grid was resampled up to a 90-meter pixel using the Avenue command RESAMPLE, and the zonal attributes (Appendix B) for those counties were calculated. The results are displayed in table 8.2.

Table 8.2 LTM-Derived Volume vs. FIA Volume for 15 Ga. Counties

County	FIA Area (1000 acres)	LTM Area (1000 acres)	FIA Volume (cu. ft.)	LTM Volume (cu. ft.)	Difference in Volume (%)
Chattahoocee*	110.8	13.9	157,084,259	23,704,917	-84.91%
Crawford*	120.4	56.7	108,213,096	159,462,498	47.36%
Harris	176.1	82.1	212,735,949	167,214,803	-21.40%
Lamar	44.6	23.8	56,120,770	65,580,164	16.86%
Macon*	72.2	37.0	165,585,632	106,701,129	-35.56%
Marion*	109.5	41.2	95,835,477	88,771,471	-7.37%
Meriwether	127.1	91.4	169,644,841	236,597,646	39.47%
Monroe*	120.3	78.1	175,816,298	210,320,237	19.62%
Muscogee*	56.7	26.1	123,264,309	46,867,862	-61.98%
Pike	40.0	24.9	61,200,094	62,638,397	2.35%
Schley*	62.1	10.2	81,167,935	22,829,350	-71.87%
Talbot	181.6	74.6	154,786,381	176,157,080	13.81%
Taylor	121.4	62.4	96,153,723	167,431,377	74.13%
Troup	91.5	71.5	175,128,164	144,934,290	-17.24%
Upson	74.4	58.8	138,907,394	154,730,361	11.39%
Totals:	**856.7**	**489.5**	**1,064,677,316**	**1,175,284,118**	**10.39%**

* Partial LTM coverage, values not incorporated into totals

Portions of six counties were located outside the LTM scene. Those counties represent only partial county-level volume estimates and were not used in the total estimates. As a point of reference, the FIA coniferous and mixed cubic-foot volume and area estimates are also listed.

Though the LTM-derived and FIA volumes appear to be similar, several things must be noted. As previously mentioned, coniferous areas were delineated using NDVIp_w. This index yields negative or slightly positive values for all non-coniferous landcover types (figure 8.13).

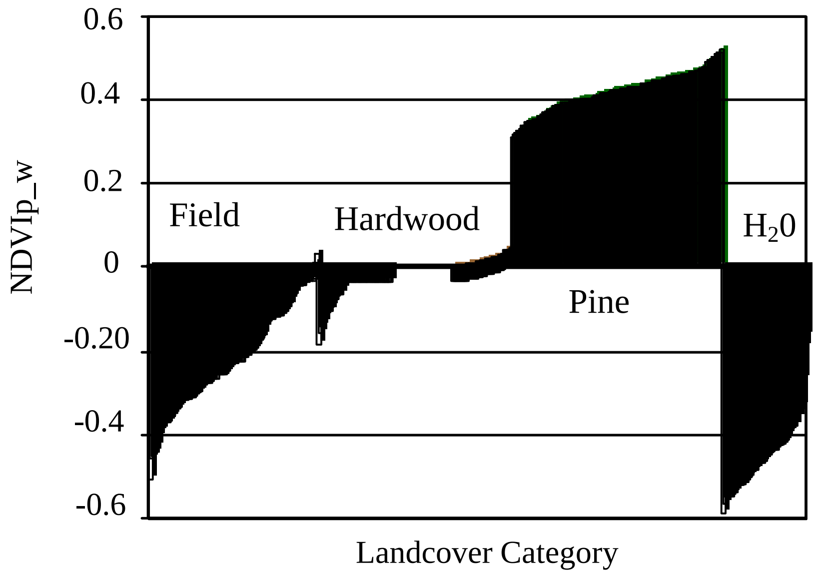

Figure 8.13 NDVIp_w Over Four Landcover Types

All NDVIp_w pixels with a value less than 0.2 were considered non-coniferous, and masked from the analysis. This assumption may exclude mixed pine-hardwood areas that were included in the FIA sample as coniferous. Second of all, the county level sampling errors associated with the FIA county-level estimates are often unacceptably high, yielding statistically unsound estimates at that level. Before an appropriate FIA estimate can be made, one may have to combine statistics from several counties (Thompson 1997).

IX. CONCLUSIONS

The objective of this research was to extend the FIA remote sensing functionality by including the ability to estimate coniferous basal area and volume using only Landsat Thematic Mapper satellite data. While doing so, several common questions regarding the use of space-borne, remotely sensed data were addressed:

(1) "Is satellite data from one season more useful than the other?",

(2) "What band or combination of bands are most useful?", and

(3) "Can one obtain volume estimates using only LTM data at the same level of accuracy the FIA program requires?"

To address these questions, simple correlations, 3 basal area, and 4 volume models were evaluated.

A. Optimal Season And LTM Band Combinations

All winter bands and summer bands 2-5, and 7 were negatively correlated with basal area, and winter bands 1-3, 5, and 7 and all summer bands were negatively correlated with volume. These results confirm the findings of Brockhaus (1992) and the Batemans Bay (Coops 1998) study. The negative relationship between the LTM data and basal area and volume can be attributed to several LTM band-dependent factors. LTM band 2, the "green" band, is sensitive to green reflectance from healthy vegetation. As the amount of healthy vegetation increases, the amount of absorbed energy increases, resulting in smaller amounts of emitted radiation captured by the satellite sensor. Due to high chlorophyll absorption in the "red" wavelengths, band 3, absorbed radiation increases as the mass of green leaves increase, emitting smaller amounts of radiation captured by the sensor. The negative relationship with the mid-infrared bands, bands 5 and 7, are driven by vegetation density, canopy shading, and leaf moisture.

LTM band 5 from both winter and summer, TM5w and TM5s, proved to be a key variable in this study. TM5w and TM5s yielded the highest single-band correlations with basal area (-0.76 and -0.81) and volume (-0.70 and -0.78). The ratio of TM5s and TM3s yielded the overall highest correlation with basal area (-0.85). The TM5 corrected summer NDVI variable, NDVIp_s, yielded the highest correlation with a ratio and volume (-0.75).

Evaluation of the basal area and volume models lend insight into the optimal season for LTM - biomass estimation. In this study, the summer LTM data yielded the model with the highest correlation with basal area. The BAs model produced an adjusted R^2 of 76.70% and predicted basal area within plus or minus 18.59% of the ground-measurements. The winter and summer combined basal area model, BAws, yielded slightly weaker results (adjusted R^2 = 74.62%, RPE = 18.98%), and the winter model, BAw, yielded much weaker results (adjusted R^2 = 58.23%, RPE = 22.19%).

Results from the LTM - volume models are not as straight forward. Volume was not successfully modeled as a function of LTM variables from a single season. While the VOLbas model, volume modeled as a function of the variables in the BAs model, yielded significant results, the relationship was considered weak (adjusted R^2 = 59.84%, RPE = 30.54%) when compared to the other multi-season models. Both the VOLoth and VOLsub models yielded strong, significant results. Each estimated volume within plus or minus 28% and had similar adjusted R^2 values, 73.14% and 70.14%, respectively.

Though basal area was effectively modeled using LTM data from a single season, multi-season models were more suited for modeling cubic-foot volume. Therefore, I recommend utilizing both "leaf-off" and "leaf-on" imagery in further research. As the prices drop, purchasing multi-season LTM data is becoming a feasible option for many. Landsat 5 Thematic Mapper satellite data can be purchased from the EROS data center for $425.00 per scene. When utilizing multi-season imagery, examining all possible combinations may not be a viable option due to time or equipment constraints. I suggest to those interested in applying these methods that they explore the short-wave mid-infrared, TM5 (1.55 - 1.75 micrometers), the near-infrared, TM4 (0.63 - 0.69 micrometers), and the red bands, TM3 (0.63 - 0.69 micrometers), as well as the possible ratios of those three variables.

B. LTM And FIA Volume Estimation

The FIA program uses sampling methods designed to achieve reliable statistics for the cluster of counties within a survey unit and at the state level (Thompson 1997). As the area or volume considered decreases in magnitude, the sampling error increases, often yielding unacceptably wide confidence intervals. FIA program leaders caution users that the accuracy of individual county data is "highly variable". Often, information from several counties must be combined before acceptable statistics are obtained.

FIA estimates for the 8 counties to which I applied the LTM-estimation procedure yielded 1.065 billion cubic feet of coniferous volume. The LTM-estimation procedures for the same 8 counties yielded 1.175 billion cubic feet, an over estimation of 110.6 million cubic feet (10.39%). At the individual county level, estimates ranged from an under prediction of 21.40% in Harris county to an over prediction of 74.13% in Taylor county (table 8.2).

The differences in volume estimation can be attributed to several factors. As stated above, FIA estimates may be unreliable at the county level due to high sampling errors. These errors ranged from 10.15% in Meriwether county to 46.92% in Troup county (Thompson 1997). The criteria by which the landscape was stratified into coniferous and nonconiferous stands, ultimately determining total conifer acreage, is another confounding factor. I utilized the NDVIp_w variable as an indicator of conifer areas. While I have found that this method was suitable for filtering pure pine stands (figure 8.13), its utility for extracting mixed pine and hardwood areas is untested. Compounding these inaccuracies is the error associated with the LTM - volume model itself. VOLsub, the model I applied to the LTM dataset in this comparison, had a relative percent error of 27.23%. This suggests that, on average, the estimates are 27.23% "off", plus or minus, from the actual measures.

The incorporation of remotely sensed data into the FIA inventory procedures would enhance the program. The USFS could address the calls for "more timely and up-to-date" data by developing remotely sensed stand parameter estimates. Currently, the landscape is stratified relative to the presence or absence of timber, and then into several specific timber type categories. The ability to stratify the landscape by volume will decrease the variability within each strata, yielding more accurate estimates while installing the same number of plots. LTM - volume estimations could also be used to update plot information not scheduled for sampling that year. In addition to increasing the timeliness of the data, the FIA program would also benefit by having a visual representation of their estimates. Currently, their map-making options are limited to interpolation-like procedures due to the non-continuous nature of the data. The LTM-estimation procedures outlined in this Thesis produce a continuous representation of the of the variable of interest.

In addition to all of the advantages of incorporating remotely sensed data into the FIA procedures, there are disadvantages that must be also considered. The one that will affect the statistics the most is the method by which coniferous and deciduous areas are delineated. Over estimation of conifer areas will result in an over estimation of the coniferous stand parameters. The method by which the model is developed must be considered, as well. The model can either be developed for each individual LTM scene, or all scenes for a state can be merged and considered as one. If the LTM scenes are processed separately, samples within each scene must be collected and a model for each must be generated. Conversely, if all scenes are processed as one, they must first be normalized to account for radiometric variations between scenes due to locational differences before they are merged and the model generated

As with all new projects, further research is needed before LTM-estimation can be considered a statistically viable option for the FIA program. Research should focus on several areas, including:

(1) the stratification of coniferous and deciduous stands into species groups,

(2) the interaction between the LTM data and those species groups, and

(3) the incorporation of other high resolution imagery and new remote sensing technologies like SAR and LIDAR.

The hierarchical relationship between the high resolution imagery and LTM lends itself to a multi-stage sampling scheme in which the landscape is stratified into general classes using LTM and then refined using the high resolution imagery. If models associating the remotely sensed variables to the new species-level classification could be developed, the accuracy of the data generated could be increased.

REFERENCES CITED

Baker, R. D. and D. V. Smith. 1970. Aerial Photograph Use In Industrial Forest Management In the South, 1970 and 1974. *Texas Forestry Paper,* School of Forestry, Stephen F. Austin State University.

Borders, B. E. 1989. Systems of Equations in Forest Stand Modeling. *Forest Science*. Volume 35, Number 2, pp. 548 - 556.

Borders, B. E., W. M. Harrison. 1996. Yield prediction and growth projection for site-prepared loblolly pine plantations in the Carolinas, Georgia, Alabama and Florida. *Plantation Management Research Cooperative, Research Paper 1996-1*. School of Forest Resources, University of Georgia, Athens, GA. 9pp.

Borders, B. E. 2001. *Estimating parameters in systems of equations*. Daniel B. Warnell School of Forest Resources, The University of Georgia. Athens, Georgia.

Brockhaus, J., S. Khorram. 1992. A comparison of SPOT and Landsat-TM data for use in conducting inventories of forest resources. *International Journal of Remote Sensing*. 13[16]:3035-3043.

Brown, L., J. M. Chen, S. G. Leblanc, J. Chilar. 2000. A Shortwave Infrared Modification to the Simple Ratio for LAI Retrieval in Boreal Forests: an Image and Model Analysis. *Remote Sensing of the Environment*. 71:16-25.

Chen, Z., C. D. Elvidge, D. P. Groeneveld. 1998. Vegetation Change Detection Using High Spectral Resolution Vegetation Indices. *Remote Sensing Change Detection*. Ann Arbor Press, Michigan. Chapter 11, 318pp.

Clark III, A., J. R. Saucier. 1990. Tables for Estimation Total–Tree Weights, Stem Weights, and Volumes of Planted and Natural Southern Pines in the Southeast. *Georgia Forest Research Paper 79*. Research Division of Georgia Forestry Commission. 23pp.

Coffee, M., H. J-H Whiffen. 2001. Traditional Industries Program in Pulp and Paper (TIP^3) Project: Quantifying Future Timber Supply: Developing a Localized, Accurate, Timely, and Cost Effective Forest Area Estimation Method, 1998 - 2000. Helen Whiffen, PI. Daniel. B. Warnell School of Forest Resources, The University of Georgia. Athens, Georgia.

Coops, N. 1998. Remote Sensing of Forest Vegetation 98. CSIRO Forestry and Forest Products project on the Spatial Prediction of Forest Productivity CDROM. Kingston, Australia.

Crist, E. P, R. C. Cicone. 1984. Application of the Tasseled Cap concept to simulated Thematic Mapper data. *Photogrammetric Engineering and Remote Sensing*. 50[3]:343-352.

Czaplewski, Ray. 1998. Use Of Advanced Remote Sensing Technologies for Annual State Inventories. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, Colorado, USA.

De Jong, S. M. 1994. Derivation of Vegetative Variables From A Landsat TM Image For Modelling Soil Erosion. *Earth Surfaces and Landforms*, 19:165-178.

Dombeck, M., S. Adams. 2000. Memorandum of Understanding between USDA Forest Service and National Association of State Foresters 2000. USDA Forest Service. http://fia.fs.fed.us/mou.rtf.

Dowdy, S., S. Wearden. 1985. *Statistics for research, 2nd edition*. John Wiley & Sons, NY. 629pp. p 469.

ESRI. 1969 - 2002. Environmental Systems Research Institute, Inc. Redlands, California. http://www.esri.com.

Evans, David. 1994. Forest Cover from Landsat Thematic Mapper Data for use in the Catahoula Ranger District Geographic Information System. *General Technical Report so-99*. Southern Forest Experiment Station, USDA Forest Service. 14pp.

FIA Plot Layout Explanation. USDA Forest Service. http://fia.fs.fed.us/library/FIA_Demo_Plot_Handout.doc.

Franklin, J., T. L. Logan, C. E. Woodcock, A. H. Strahler. 1986. Coniferous Forest Classification and Inventory Using Landsat and Digital Terrain Data. *IEEE Transactions on Geoscience and Remote Sensing*. 24[1]:139-149.

Franklin, S. E. 2001. *Remote Sensing for sustainable forest management*. Lewis Publishing, Boca Raton. 407 pages.

GeoScience Australia. 2002. Australia National Mapping Division. http://www.auslig.gov.au/acres/prod_ser/landdata.htm.

Gillespie. 2000. Forest Inventory and Analysis 2000 Business Summary. USDA Forest Service. http://www.ncrs.fs.fed.us/pubs/misc/Gillespie-p-00.pdf

Heller, R. C., R. V. Bega. 1973. Detection of Forest Diseases by Remote Sensing. *The Journal of Forestry*. 71:1.

Horler, D. N. H., F. J. Ahern. 1986. Forestry Information Content of Thematic Mapper Data. *International Journal of Remote Sensing*. 7[3]:405-428.

Jakubauskas, M. E., K. P. Price. 1994. Landsat Thematic Mapper Characterization of Coniferous Forest Succession. *Proceedings of the 1994 ASPRS-ACSM Annual Meeting,* Reno, NV, pp 256-267.

Kauth, R. J., G. S. Thomas. 1976. The Tasseled Cap - A graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. *Proceedings of the Symposium on Machine Processing of Remotely Sensed Data*, Perdue University, IN, pp. 4B41 - 4B51.

King, S. L., A. J. Lister, M. Hoppus. 2000. A comparison of kriging and cokriging for mapping forest volume in Connecticut. *Proceedings of SOFOR GIS 2000: The 3rd Southern Forest Resources GIS Conference*. The Center for Continuing Education, The University of Georgia, Athens, Georgia.

Landreth, J. 2002. Masters Thesis, "Comparing the Use of Synthetic Aperture RADAR and Landsat Thematic Mapper to Predict Slash Pine (*Pinus Elliottii*) Plantation Attributes. Daniel B. Warnell School of Forest Resources, The University of Georgia. Athens, Georgia.

Landsat TM Metadata. USGS Earth Resoruces Observation Systems Data Center. http://edc.usgs.gov/glis/hyper/guide/landsat_tm

Lashbrook, J., R. Williams, J. Nichols, R. Heiligmann, B. Motsch, R. Romig, J. Vimmerstedt. 2001. The Application of Remote Sensing to the Inventory of White Pine (*Pinus Strobus* L.) in Eastern Ohio. *Ohio Agricultural Research and Development Center, Research Bulletin 1194*. Ohio State University. 13pp.

Lillesand, T. M. and R. W. Kiefer. 1994. *Remote Sensing and Interpretation 3rd Edition* John Wiley and Sons. 748 pp.

Meyer, M., N. Miller, R. Hackett. 1981. Application of 35mm aerial photography to forest land use change analysis in the upper peninsula of Michigan. *IAFHE Research Report 81-2*.

Nemani, R., L. Pierce, S. Running, and L. Band. 1993. Forest ecosystem processes at the watershed scale: Sensitivity to remotely-sensed Leaf Area Index estimates. *International Journal of Remote Sensing* 14[13]:2519-2534.

Oladi, Djafar 2001. Developing a Forest Growth Monitoring Model Using Themaitc Mapper Imagery. Presented at the 22nd Asian Conference on Remote Sensing, 5 - 9 November 2001, Singapore. Centre for Remote Imaging, Sensing and Processing (CRISP), National University of Singapore.

Phelps, B. L. 2001. Masters Thesis, "Predicting Pine Basal Area Using LTM data in the Coastal Plain of Georgia". Daniel B. Warnell School of Forest Resources, The University of Georgia. Athens, Georgia.

Reid, E. H., G. D. Pickford. 1942. An appraisal of range survey methods from the standpoint of effectiveness range management. *Range Resources Paper Number 2*. US department of Agriculture, Forest Service, Pacific Northwest, Portland, OR. 66 p.

SAS Institute Inc. 1993. SAS/ETS *Users Guide, Version 6, Second Edition*. SAS Institute Inc., Cary, NC. 1022pp.

Shiver, B. D., B. E. Borders, 1996. *Sampling techniques for forest resource inventory.* John Wiley & Sons, Inc., New York. 356pp.

Stark, P. B 2002. SticiGui: Statistics Tools for Internet and Classroom Instruction with a Graphical User Interface. Department of Statistics, University of California, Berkeley. http://stat-www.berkeley.edu/users/stark/SticiGui/index.htm.

Thompson, M. T. 1997. Forest Statistics for Georgia, 1997. *USDA Forest Service Southern Research Station Resource Bulletin SRS-36*. Asheville, NC. 92 pp.

Trimble. 1978 - 2002. Trimble Navigation Limited. Sunnyvale, California. http://www.trimble.com.

Trotter, C. M., J. R. Dymond, C. J. Goulding. 1997. Estimation of timber volume in a coniferous plantation forest using Landsat TM. *International Journal of Remote Sensing.* 18[10]:2209-2223.

Turner, D. P, Warren B. Cohen, R. E. Kennedy, K. S. Fassnacht, J. M. Briggs. 1999. Relationship between Leaf Area Index and Landsat TM Spectral Vegetation Indices across Three Temperate Zone Sites. *Remote Sensing of the Environment*. 70:52-68.

TVA . 2002. Tennessee Valley Authority. http://www.tva.gov/index.htm.

USDA Forest Service. 2001. Forest inventory and analysis national core field guide, volume 1: field data collection procedures for phase 2 plots, version 1.5. U.S. Department of Agriculture, Forest Service, Washington Office. Internal report. On file with: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis, 201 14th St., Washington, D.C., 20250.

Ustin, S. L., D. A. Roberts, Q. J. Hart. 1998. Seasonal Vegetation Patterns in a CaliforniaCoastal Savanna Derived from Advanced Visible/Infrared Imaging Spectrometer (AVRIS) Data. *Remote Sensing Change Detection*. Ann Arbor Press, Michigan. Chapter 10, 318pp.

Vogelmann, J. E. 1990. Comparison Between Two Vegetation Indices for Measuring Different Types of Forest Damage in the North-Eastern Unites States. *International Journal of Remote Sensing*. 11[12]:2281-2297.

Wagner, M. J. 1997. Improving Road Management with GIS. *Earth Observation Magazine*, June 1997, pp 21 - 26.

Williams, R. E., C. D. Leaphart. 1978. A system using aerial photography to estimate area of root disease centers in forests. Canadian Journal of Forest Research, Volume 8, number 2, 1978, pages 214 - 219

Wilson, J. D. 1995. GIS and Forestry, The Poor Cousin Comes of Age. *Earth Observation Magazine*, September 1995, pp 16 -20.

Zuuring, H. 2001. General Remote Sensing Principles - Part 2. *Online Class Notes: GIS Methods & Applications I.* The University of Montana School of Forestry, Missoula, Montana. http://www.forestry.umt.edu/academics/courses/FOR503/rs2.htm.

APPENDIX A. FIA PHASE II ITEMS

Core optional variables are in italics. n/a is not applicable.

Variable Name	Tolerance	MQO	Values	Units
Plot Level Data				
STATE	No errors	at least 99% of the time	Appendix 1	n/a
COUNTY	No errors	at least 99% of the time	Appendix 1	n/a
PLOT NUMBER	No errors	at least 99% of the time	0001 to 9999	n/a
SAMPLE KIND	No errors	at least 99% of the time	1 to 3	n/a
MANUAL VERSION	No errors	at least 99% of the time	1.1 and higher	n/a
YEAR	No errors	at least 99% of the time	Beginning with 1998, constant for a given year	year
MONTH	No errors	at least 99% of the time	Jan – Dec	month
DAY	No errors	at least 99% of the time	01 to 31	day
DECLINATION	*No errors*	*at least 99% of the time*	*-359.0 to 359.0*	*degrees*
TRAILS OR ROADS	No errors	at least 90% of the time	0 to 5	n/a
HORIZONTAL DISTANCE TO IMPROVED ROAD	No errors	at least 90% of the time	1 to 9	n/a
ROAD ACCESS	No errors	at least 90% of the time	0 to 4, 9	n/a
PUBLIC USE RESTRICTIONS	No errors	at least 90% of the time	0 to 3, 9	n/a
RECREATION USE 1	No errors	at least 90% of the time	0 to 7, 9	n/a
RECREATION USE 2	No errors	at least 90% of the time	0 to 7, 9	n/a

Variable Name	Tolerance	MQO	Values	Units
RECREATION USE 3	No errors	at least 90% of the time	0 to 7, 9	n/a
WATER ON PLOT	No errors	at least 90% of the time	0 to 5, 9	n/a
QA STATUS	No errors	at least 99% of the time	1 to 7	n/a
CREW TYPE	No errors	at least 99% of the time	1, 2	n/a
GPS UNIT	No errors	at least 99% of the time	0 to 4	n/a
GPS SERIAL NUMBER	No errors	at least 99% of the time	000001 to 999999	n/a
COORDINATE SYSTEM	No errors	at least 99% of the time	1,2	n/a
LATITUDE	+/- 140 ft	at least 99% of the time		degrees, seconds
LONGITUDE	+/- 140 ft	at least 99% of the time		degrees, seconds
UTM ZONE	No errors	at least 99% of the time	03-19Q and 03-19W	
EASTING (X) UTM	+/- 140 ft	at least 99% of the time		
NORTHING (Y) UTM	+/- 140 ft	at least 99% of the time		
AZIMUTH TO PLOT CENTER	+/- 3 degrees	at least 99% of the time	000 at plot center 001 to 360 not at plot center	degrees
DISTANCE TO PLOT CENTER	+/- 6 ft	at least 99% of the time	000 at plot center 001 to 200 if a Laser range finder not used 001 to 999 if a Laser range finder is used	feet
GPS ELEVATION		at least 99% of the time	-00100 to 20000	feet
GPS ERROR	No errors	at least 99% of the time	0 to 70 if possible 71 to 999 if an error < 70 cannot be obtained	feet

Variable Name	Tolerance	MQO	Values	Units
NUMBER OF READINGS	No errors	at least 99% of the time	1 to 999	n/a
GPS FILENAME	*No errors*	*at least 99% of the time*	*English, alpha-numeric*	*n/a*
PLOT-LEVEL NOTES	n/a	n/a	English, alpha-numeric	n/a
P3 HEXAGON NUMBER	No errors	at least 99% of the time		n/a
P3 PLOT NUMBER	No errors	at least 99% of the time	1 to 9	n/a
Condition Class Information				
CONDITION CLASS NUMBER	No errors	at least 99% of the time	1 to 9	n/a
CONDITION CLASS STATUS	No errors	at least 99% of the time	1 to 7	n/a
RESERVED STATUS	No errors	at least 99% of the time	0, 1	n/a
OWNER GROUP	No errors	at least 99% of the time	10, 20, 30, 40	n/a
FOREST TYPE	No errors	at least 99% of the time in group at least 95% of the time in type	Appendix 2	n/a
STAND SIZE CLASS	No errors	at least 99% of the time	0 to 6	class
REGENERATION STATUS	No errors	at least 99% of the time	0, 1	n/a
TREE DENSITY	No errors	at least 99% of the time	1 to 3	n/a
OWNER CLASS	No errors	at least 99% of the time	11-13; 21-25; 31-33; 41-45	class
PRIVATE OWNER INDUSTRIAL STATUS	No errors	at least 99% of the time	0, 1	n/a
ARTIFICIAL REGENERATION SPECIES	No errors	at least 99% of the time	Appendix 4	n/a

Variable Name	Tolerance	MQO	Values	Units
STAND AGE	+/- 10%	at least 95% of the time	000 to 997, 998, 999	year
DISTURBANCE 1	No errors	at least 99% of the time	00; 10; 20; 30-32;40-46; 50-54; 60; 70; 80	n/a
DISTURBANCE YEAR 1	+/- 1 year for 5-year measure. cycles +/ 2years for > 5-year measure. cycles	at least 99% of the time	Since the previous plot visit, or the past 5 years for plots visited for the first time; 9999 if disturbance occurs continuously over time	year
DISTURBANCE 2	No errors	at least 99% of the time	00; 10;20; 30-32;40-46; 50-54; 60; 70; 80	n/a
DISTURBANCE YEAR 2	+/- 1 year for 5-year measure. cycles +/ 2years for > 5-year measure. cycles	at least 99% of the time	Since the previous plot visit, or the past 5 years for plots visited for the first time; 9999 if disturbance occurs continuously over time	year

Variable Name	Tolerance	MQO	Values	Units
DISTURBANCE 3	No errors	at least 99% of the time	00; 10;20; 30-32;40-46; 50-54; 60; 70; 80	n/a
DISTURBANCE YEAR 3	+/- 1 year for 5-year measure. cycles +/ 2years for > 5-year measure. cycles	at least 99% of the time	Since the previous plot visit, or the past 5 years for plots visited for the first time; 9999 if disturbanc e occurs continuou sly over time	year
TREATMENT 1	No errors	at least 99% of the time	00, 10, 20, 30, 40, 50	n/a
TREATMENT YEAR 1	+/- 1 year for 5-year measure. cycles +/- 2 years for >5-year measure. cycles	at least 99% of the time	Since the previous plot visit, or the past 5 years for plots visited for the first time	year
TREATMENT 2	No errors	at least 99% of the time	00, 10, 20, 30, 40, 50	n/a
TREATMENT YEAR 2	+/- 1 year for 5-year measure. cycles +/- 2 years for >5-year measure. cycles	at least 99% of the time	Since the previous plot visit, or the past 5 years for plots visited for the first time	year
TREATMENT 3	No errors	at least 99% of the time	00, 10, 20, 30, 40, 50	n/a

Variable Name	Tolerance	MQO	Values	Units
TREATMENT YEAR 3	+/- 1 year for 5-year measure. cycles +/- 2 years for >5-year measure. cycles	at least 99% of the time	Since the previous plot visit, or the past 5 years for plots visited for the first time	year
PHYSIOGRAPHIC CLASS	No errors	at least 80% of the time	xeric: 11, 12, 13, 19 mesic: 21, 22, 23, 24, 25, 29 hydric: 31, 32, 33, 34, 35, 39	n/a
PAST NONFOREST / INACCESSIBLE LAND USE	No errors	at least 99% of the time	10-15; 20; 30-33; 40; 90-94	n/a
PRESENT NONFOREST LAND USE	No errors	at least 99% of the time	10-15; 20; 30-33; 40; 90-94	n/a
NONFOREST YEAR	+/- 1 year for 5-year measure. cycles +/- 2 years for > 5-year measure. cycles	at least 70% of the time	1999 or higher	year
Boundary Data				
SUBPLOT NUMBER	No errors	at least 99% of the time	1 to 4	n/a
PLOT TYPE	No errors	at least 99% of the time	1 to 3	n/a
BOUNDARY CHANGE	No errors	at least 99% of the time	0 to 3	n/a
CONTRASTING CONDITION	No errors	at least 99% of the time	1 to 9	n/a
LEFT AZIMUTH	+/- 10 degrees	at least 90% of the time	001 to 360	degrees

Variable Name	Tolerance	MQO	Values	Units
CORNER AZIMUTH	+/- 10 degrees	at least 90% of the time	000 to 360	degrees
CORNER DISTANCE	+/- 1 ft	at least 90% of the time	microplot: 1 to 7 subplot: 1 to 24 annular plot: 1 to 59	feet
RIGHT AZIMUTH	+/- 10 degrees	at least 90% of the time	001 to 360	degrees
Subplot Information				
SUBPLOT NUMBER	No errors	at least 99% of the time	1 to 4	n/a
SUBPLOT CENTER CONDITION	No errors	at least 99% of the time	1 to 9	n/a
MICROPLOT CENTER CONDITION	No errors	at least 99% of the time	1 to 9	n/a
SUBPLOT SLOPE	+/- 10 %	at least 90% of the time	000 to 155	percent
SUBPLOT ASPECT	+/- 10 degrees	at least 90% of the time	000 to 360	degrees
SNOW/WATER DEPTH	+/- 0.5 ft	At the time of measurement	0.0 to 9.9	feet
SUBPLOT/ANNULAR PLOT STATUS	No errors	at least 99% of the time	0, 1	n/a
SUBPLOT/ANNULAR PLOT CONDITION LIST	*No errors*	*at least 99% of the time*	*1000 to 9876*	*n/a*
Tree and Sapling Data				
SUBPLOT NUMBER	No errors	at least 99% of the time	1 to 4	n/a
TREE RECORD NUMBER	No errors	at least 99% of the time	000, 001 to 999	n/a
CONDITION CLASS NUMBER	No errors	at least 99% of the time	1 to 9	n/a

Variable Name	Tolerance	MQO	Values	Units
AZIMUTH	+/- 10 degrees	at least 90% of the time	001 to 360	degrees
HORIZONTAL DISTANCE	microplot:+/- 0.2ft subplot: +/- 1.0 ft annular plot: +/- 3.0 ft	at least 90% of the time	microplot: 00.1 to 6.8 subplot: 00.1 to 24.0 annular plot: 00.1 to 58.9	feet
TREE STATUS	No errors	at least 95% of the time	0 to 4	n/a
NEW TREE RECONCILE	No errors	at least 95% of the time	1 to 4	n/a
MORTALITY	*No errors*	*at least 85% of the time*	*0, 1*	*n/a*
LEAN ANGLE	No errors	at least 99% of the time	0, 1	n/a
SPECIES	No errors	at least 99% of the time for genus at least 95% of the time for species	Appendix 4	n/a
DIAMETER	+/- 0.1 inch per 20 inches of diameter on trees with a measured diameter	at least 95% of the time	0001 to 9999	inches
DIAMETER CHECK	No errors	at least 99% of the time	0 to 2	n/a
ROTTEN / MISSING CULL	+/- 10%	at least 90% of the time	0 to 99	percent
TOTAL LENGTH	+/- 10% of true length	at least 90% of the time	005 to 400	feet
ACTUAL LENGTH	+/- 10% of true length	at least 90% of the time	005 to 400	feet
LENGTH METHOD	No errors	at least 99% of the time	1 to 3	n/a
CROWN CLASS	No errors	at least 85% of the time	1 to 5	n/a
UNCOMPACTED LIVE CROWN RATIO	+/- 10%	at lest 90% of the time	00 to 99	percent

Variable Name	Tolerance	MQO	Values	Units
COMPACTED CROWN RATIO	+/- 10%	at least 80% of the time	00 to 99	percent
DAMAGE LOCATION 1	+/- 1 location class	at least 80% of the time	0 to 9	class
DAMAGE TYPE 1	No errors	at least 80% of the time	1-5; 11-13; 20-25; 31	n/a
DAMAGE SEVERITY 1	No errors	at least 80% of the time	Defined for each DAMAGE TYPE	class
DAMAGE LOCATION 2	+/- 1 location class	at least 80% of the time	0 to 9	class
DAMAGE TYPE 2	No errors	at least 80% of the time	1-5; 11-13; 20-25; 31	n/a
DAMAGE SEVERITY 2	No errors	at least 80% of the time	Defined for each DAMAGE TYPE	class
CAUSE OF DEATH	No errors	at least 80% of the time	10 to 90	n/a
MORTALITY YEAR	+/- 1year for 5-year measure. cycles +/- 2years for > 5-year measure. cycles	at least 70% of the time	1995 or higher	year
DECAY CLASS	+/- 1 class	at least 90% of the time	1 to 5	class
UTILIZATION CLASS	No errors	at least 99% of the time	0, 1	n/a
LENGTH TO DIAMETER MEASUREMENT POINT	*+/- 0.2 ft*	*at least 90% of the time*	*0.1 to 15.0*	*inches*
PERCENT ROUGH CULL	*+/- 10 %*	*at least 90% of the time*	*00 to 99*	*percent*
MISTLETOE CLASS	*+/- 1 class*	*at least 90% of the time*	*0 to 6*	*class*

Variable Name	Tolerance	MQO	Values	Units
TREE NOTES	n/a	n/a	English, alpha-numeric	n/a
Seedling Data				
SUBPLOT NUMBER	No errors	at least 99% of the time	1 to 4	n/a
SPECIES	No errors	at least 99% of the time for genus at least 95% of the time for species	Appendix 4	n/a
CONDITION CLASS				
SEEDLING COUNT	No errors	at least 95% of the time	1 to 5 exact count 6 more than 5 individuals by species by condition class	number
Site Tree Information				
CONDITION CLASS LIST	No errors	at least 99% of the time	1 to 9 or 10000 to 98765	n/a
SPECIES	No errors	at least 99% of the time for genus at least 95% of the time for species	Appendix 5	n/a
DIAMETER	+/- 0.1 inch per 20 inches of diameter on trees with a measured diameter	at least 95% of the time	0001 to 9999	inches
SITE TREE LENGTH	+/- 10% of true length	at least 90% of the time	001 to 999	feet
TREE AGE AT DIAMETER	+/- 5 years	at least 95% of the time	001 to 999	year

Variable Name	Tolerance	MQO	Values	Units
SITE TREE NOTES	n/a	n/a	English, alpha-numeric	n/a
SUBPLOT NUMBER	*No errors*	*at least 99% of the time*	*1 to 4*	*n/a*
AZIMUTH	*+/- 10 degrees*	*at least 90% of the time*	*001 to 360*	*degrees*
HORIZONTAL DISTANCE	*+/-5 ft*	*at least 90% of the time*	*000.1 to 200.0*	*feet*

APPENDIX B. ZONAL ATTRIBUTES AVENUE SCRIPT

```
theView = av.GetActiveDoc
theThemeList = theView.getThemes
polyList = list.make
gridList = list.make
'***** Find all poly Themes and put them in "polyList"
for each t in theThemeList
  if (t.Is(FTheme)) then
    if (t.getFTab.GetShapeClass.GetClassName = "polygon") then
      polyList.add(t)
      polyList(t).setActive(false)
    end
  end
'***** Find all grid Themes and put them in "gridList"
  if (t.Is(GTheme)) then
    gridList.add(t)
    gridList(t).setActive(false)
  end
end
'***** Select the zone Theme, the Poly, and grid Themes
zoneTheme = msgBox.listAsString(polyList,"Select the Polygon Theme","")
'valueTheme = msgBox.listAsString(gridList,"Select the Grid Theme","")
hinfo = msgBox.Info("Analysis Cell Size set to 0.5.","FYI")
for each g in gridList
  valueTheme = g
  art = Nil
  'Grid.SetAnalysisExtent(#GRID_ENVTYPE_MAXOF,art)
  Grid.SetAnalysisCellSize(#GRID_ENVTYPE_VALUE, 0.5)
'***** the zoneObj is the vector polygon theme
  zoneObj = zoneTheme.GetFTab
'***** get zone Field from zoneObj
  zoneField = zoneObj.FindField("uid")
'***** obtain grid from value theme and create VTab
  theGrid = valueTheme.GetGrid
  aPrj = theView.GetProjection
'***** create a text file name corresponding to the grid theme name
  baseName = valueTheme.GetName.AsString
  fileExt = ".dbf".AsString
'***** concatenate baseName and fileExt
  vname = (baseName + fileExt).AsString
  aFN =  (baseName + fileExt).asFileName
```

```
'***** calculate the zonal stats table
  vname = theGrid.ZonalStatsTable(zoneObj,aPrj,zoneField,FALSE,aFN)
'***** check for error during operation
  if (vname.HasError) then
    return NIL
  end
  ZoneAttTable = Table.Make(vname)
  ZoneAttTable.GetWin.Activate
'***** create an alias for the field name
  aliasMean = (baseName + ("_Mean").AsString).AsString
'***** make all fields in the table invisible
  theTable = av.GetActiveDoc.GetVTab
  for each f in theTable.GetFields
    f.SetVisible(false)
  end
'***** make the index and mean visible in the table
  theTable.FindField("uid").SetVisible(true)
  theTable.FindField("Mean").SetVisible(true)
  theTable.FindField("Mean").SetAlias(aliasMean)
'***** this is the table that will be joined to the Attribute table
  vtab1 = ZoneAttTable.GetVTab
  field1 = vtab1.FindField("uid")
'***** this is the Attribute Table of... that will have data joined to
'***** zoneObj = zoneTheme.GetFTab
  aToField = zoneObj.FindField("uid")
'***** Join the vtab1, using field1 to aToField
  zoneObj.Join(aToField,vtab1,field1)
end
```