USING REMOTELY SENSED DATA TO MAP FOREST AGE CLASS BY COVER TYPE IN EAST TEXAS

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Abstract

The overall goal of the project was to test a methodology to accurately quantify the forest resources of East Texas based on the premise that the quantification and qualification of forest resources is crucial to: (1) managing the resources wisely by providing timely and accurate information; and (2) proper forest resource assessment is crucial to the economic development and sustainability of East Texas communities. Current forest composition information was derived using Landsat ETM+ data and traditional unsupervised classification methodology. Current forest age class determination was obtained by spatial modeling within a Boolean format forest/non-forest cover type maps created using unsupervised classification methodology as derived from Landsat ETM+, TM and MSS data collected in five year intervals from 1972 until 2002.

Key Words: Landsat, Accuracy, Land Cover, Age

Introduction

The overall goal of the project was to test a methodology to accurately quantify the forest resources of East Texas based on the premise that the quantification and qualification of forest resources is crucial to: (1) managing the resources wisely by providing timely and accurate information; and (2) proper forest resource assessment is crucial to the economic development and sustainability of East Texas communities.

Prior quantification and qualification of forest resources in East Texas have relied on measurements taken at field plots recorded either by the Texas Forest Service (TFS) or the United States Forest Service (USFS) via the Southern Forest Inventory and Analysis Program (SFIA). However, for field plot measurements to be effective with respect to time and cost, plots must be physically located with data collected and analyzed in a timely manner. Inaccessible or remote areas, required to validate sampling procedures, may prove difficult to measure.

Satellite based remote sensing, which has the ability to acquire information about earth's resources from a distance, can provide accurate information concerning forested resources in a more timely manner due to high temporal resolution and synoptic perspective (Campbell 2002). Satellite based remotely sensed data for natural resources, available since 1972 (Lauer et al. 1997), can provide a historical perspective of resources, as well as forest composition maps (Jensen 1996), forest age class assessments (Sader et al. 2003) and biometric measurements in a timely and repetitive manner (Lefsky et al. 1999). Hence, this study was initiated to assess value of remote sensed (satellite) data for rapid assessment of important forest resource attributes.

Objectives

Project objectives were to develop a methodology for mapping the forest resources of East Texas into: (1) classification of current forest composition by cover type; and (2) classification of forest classes by age class distribution. Constraints for the derived methodology dictated that the quantification of forest cover types and age class distributions must, 1) be derived using standardized and readily available data, 2) be repeatable within a timely manner and 3) be cost-effective.

Methodology and Results

The project was tested in a 4-county area of East Texas encompassing Nacogdoches, Angelina, Shelby and San Augustine counties (Figure 1). The methodology was divided into

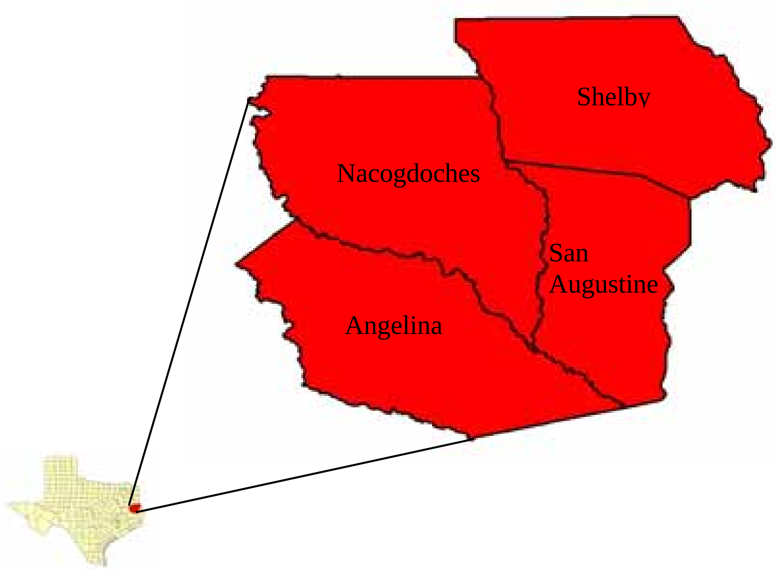

Figure 1. Location of 4-county study area in East Texas.

two distinct phases. Phase one involved the production of a forestland cover map, and Phase two involved creation of an age class distribution map stratified by forest cover type for the 4-county area.

Phase One

Twenty-two geometrically corrected Landsat Scenes (*i.e.*, 2 Landsat ETM+ scenes, 11 Landsat TM scenes and 9 Landsat MSS scenes) encompassing the 4-county project area were acquired from the U.S. Geological Survey's (USGS) EROS Data Center in Sioux Falls, SD. Scenes acquired involved obtaining leaf-on (summer) and leaf-off (winter) scenes approximately every 5-years from 1974 thru 2002. Dates for image acquisition included 2002, 1997, 1992, 1987, 1984, 1980 and 1974. A visual assessment of each image was performed to determine image quality and to verify general geometric accuracy. A combination of winter and summer scenes were obtained to produce a composite image per 5-year cycle to aid in classification differentiation of hardwood areas.

Each image was radiometrically corrected via histogram subtraction to decrease atmospheric haze and provide the classification software with imagery representing a truer spectral signature of feature objects (Jensen 1996, Teillet 1986). In addition, any clouds present in the imagery were removed and replaced with clear imagery from a similar acquisition date and solar zenith angle.

All imagery were acquired precision terrain corrected to the UTM coordinate system using a 30-meter pixel. Verification of image registration was obtained via a visual assessment by comparing each image, assumed to be the most current leaf-off scene from 2002 (*i.e.*, the most currently available satellite imagery for the project area), to a project base map composed of Texas Digital Orthographic Quarter Quadrangles (TxDOQQ) from the Texas Natural Resources Information System (TNRIS) Strategic Mapping (STRATMAP) program, at 30 systematically chosen points within each image. In addition, to minimize confusion in the classification process between rural and urban forest cover types, all pixels falling within an urban environment were masked to increase classification accuracy.

Summer and winter scenes for 2002, representing the most currently available data for the study area, were combined to create a composite image that then was classified into 100 initial classes using unsupervised classification methodology (Campbell 2002, Jensen 1996, Jahne 1991). Constraints in the classification procedure called for 100 classification clusters, a convergence threshold of 97.5% and 50 iterations (*i.e.,* to ensure the convergence threshold stopped the iterative ISODATA classification procedure and not the number of classification iterations). The 100 initial classes then were recoded to represent 5 distinct cover types of interest: non-forest, regeneration, pine, hardwood, and mixed pine-hardwood forest in the project area (Figure 2). A summary of the acres per cover type indicated the 4-county project area encompasses 2,096,041 ac. (848, 600 ha.), with pine being the dominant forest cover type in each of the 4-counties.

Accuracy of the 2002 baseline cover type map was assessed through a traditional site specific error matrix by comparing *in-situ* land cover assessment with corresponding land classifications at 518 stratified points in the 4-county area (Congalton 1991, Congalton et al. 1983). Results from the site specific accuracy assessment indicated the 2002 land cover map had an overall accuracy of 72.78%; variable users and producers accuracies per individual cover type and a kappa statistic of 62.51% suggesting the accuracy of the baseline map was 62.51%, better than one would expect by chance.

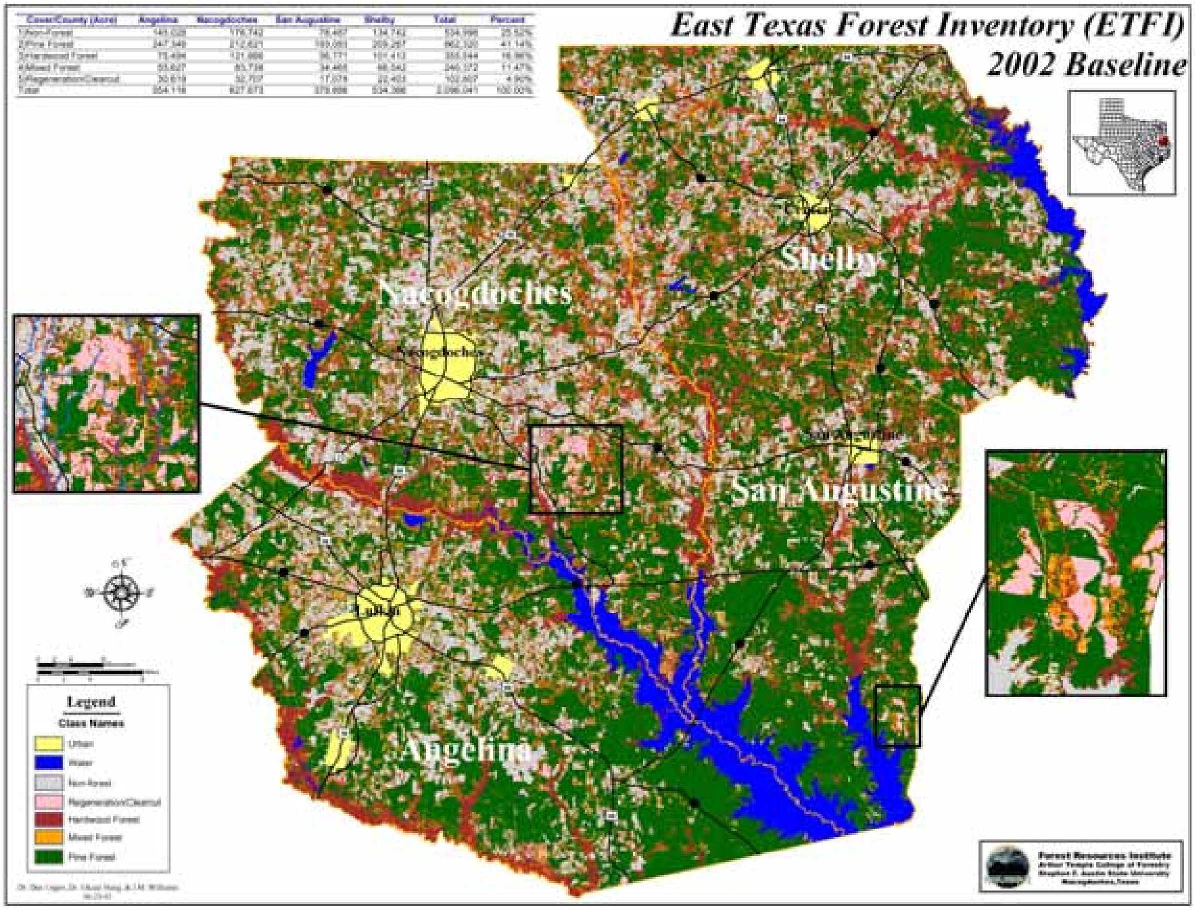

Figure 2. 2002 Land Cover Map.

To verify classification methodology and to assess relative accuracy of overall acreage (hectares), a non-site specific assessment described by Campbell (2002) was performed by comparing classified forested acreage totals to forest acreage assessment data obtained from USFS FIA program for the 4-county area. Results indicated the 2002 baseline forest acreage was within 4.4% agreement with 1988 FIA acreage data; 1987 classified forest acreage was within 0.5% agreement with 1988 FIA acreage data; and 1980 classified forest acreage is within 7.4% agreement with 1980 FIA acreage data.

Phase Two

Creation of an age class distribution map for each forestland cover type derived in the 2002 land cover base map (*i.e.*, pine, hardwood, mixed pine-hardwood) first involved combining the winter and summer time scenes for each approximate 5-year interval represented by image acquisition dates (*i.e.*, 1997, 1992, 1987, 1984, 1980 and 1974). Once combined per approximate 5-year interval, each combined image then was classified into 100 initial classes using traditional unsupervised classification methodology (Campbell 2002, Jensen 1996, Jahne 1991). Constraints in the classification procedure called for 100 classification clusters, a percentage breakdown of 97.5% and 50 iterations (*i.e.*, to ensure the number of iterations stopped the iterative ISODATA classification procedure).

Once classified, all 100 initial classification categories then were recoded into two unique classes, creating binary maps representing forest (value = 1) or non-forest (value = 0) pixels. The binary maps of forest/non-forest pixels for each approximate 5-year interval, as well as the 2002 baseline forest cover type map recoded to a forest/non-forest bitmap condition, were imported into a spatial model created to identify age of each individual pixel (ERDAS 1997). The spatial model identified age of each pixel thru Boolean manipulation, whereby if the value of any given pixel location remained a constant value of forest over time (value = 1), pixel age then must be equal to or greater than the date of the oldest available satellite imagery for the project. Conversely, if a mid-aged pixel was identified as a non-forest pixel, the spatial model via Boolean manipulation would identify the age of that pixel location as the age associated with the next available date for a forest pixel for that given location (ERDAS 1997).

The spatial model, via its Boolean manipulations, created 7 age class distributions within the project area corresponding to approximate 5-year intervals. All 7-age classes then were recoded to create 5 age class distributions representing age classes that most represent the growing stages of forest resources in East Texas. Final age class distributions represented forest conditions less than 5 years old, 5 to less than 15 years old, 15 to less than 22 years old, 22 to less than 28 years old and greater than or equal to 28 years of age. In addition to creating 5 distinct forest land cover age classes, the spatial model also was written so the most recent forest binary map from 1997 was combined with the non-forest land cover portion from the 2002 land cover base map to derive a forest regeneration category. This was defined as areas considered forest in 1997, but were classified as non-forest in 2002.

The 2002 baseline land cover map was combined with the map of 5 distinct age classes of forest land cover to derive a final age distribution per cover type which encompassed 19 classes: urban, water, non-forest, regeneration and 5 unique age classes per pine, hardwood and mixed pine-hardwood forest cover type (Figure 3). A summary of the number of acres per cover type stratified by age within the 4-county area indicated pine was the dominant cover type by percent age cover within each county; and, the overriding age of the majority of any given forest cover type was greater than or equal to 28 years.

The accuracy of the age class distribution map was assessed through a traditional site specific error matrix by comparing *in-situ* age assessments with corresponding Boolean derived age at 518 stratified points in the 4-county area (Congalton 1991, Congalton et al. 1983). Results from the site specific accuracy assessment indicated the age class distribution map had an overall accuracy of 58.69%, variable users and producers accuracies per individual age class and a kappa statistic of 45.82%. This indicated that the accuracy of the age class distribution per cover type classification category was 45.82%; better than one would expect by chance.

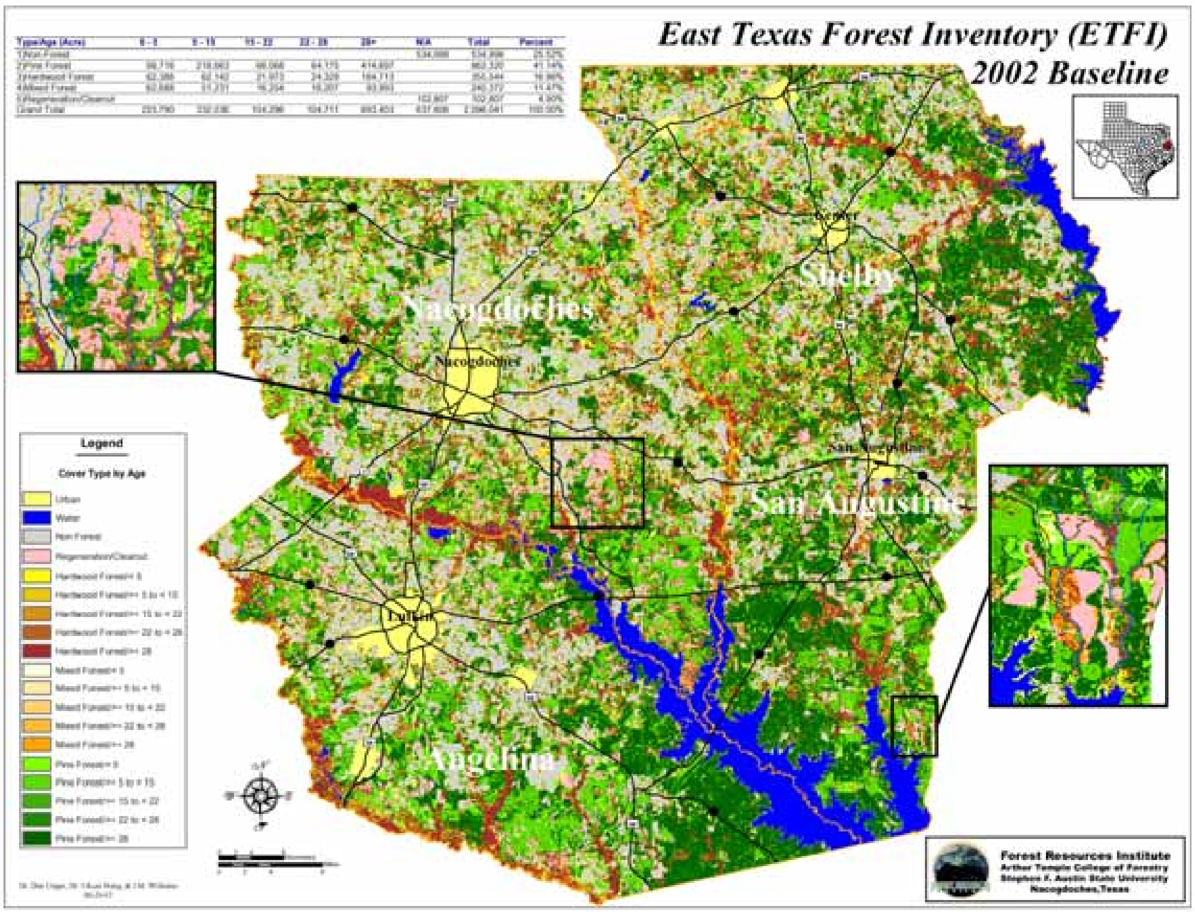

Figure 3. Map of 2002 Land Cover Stratified by Age.

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