

ABOVE-GROUND BIOMASS ESTIMATION IN A FORESTLAND USING A LANDSAT THEMATIC MAPPER IMAGE WITH SUPERVISED REGRESSION ANALYSIS

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ABSTRACT

Due to the carbon budget trading framework incorporated in the Kyoto Protocol, techniques for cost- and time-efficient above-ground biomass (AGB) estimation on forestlands may be necessary. Using remotely sensed images, such as a Landsat Thematic Mapper (TM) image, it should be possible to estimate AGB with satisfactory accuracy, compared to AGB estimation through conventional field measurements. The proposed research will focus on two major objectives regarding AGB estimation using a TM image of the Whitehall Forest in Athens, Georgia. The first objective will focus on the establishment of the relationships between spectral reflectance values in radiometric wavelengths extracted from a sub-scene of a TM image and AGB through the conventional field measurements using supervised regression analysis as an image classification method. The accuracy level of AGB estimation models derived through regression analysis will be assessed using the coefficient of determination (R^2) between estimated and measured AGB.

Although supervised regression analysis requires a minimal number of measured AGB data points from the research area, few studies have intensively examined the relationship between required amount of AGB reference data and accuracy levels in AGB estimation. Therefore, the second objective of this research will be to assess how much AGB reference data is needed to attain a certain accuracy level in AGB estimation using a single TM image.

KEYWORDS. Landsat TM, image classification, remote sensing, sampling.

INTRODUCTION

Since the beginning of the Landsat Project, led by mainly NASA and U.S. Geological Survey in 1972, numerous types of satellite imagery have been utilized for a variety of natural resource management purposes. Given that satellite imagery has been used to classify vegetation, it is not unreasonable to assure that there is a possibility of using Landsat TM imagery to estimate the above-ground biomass (AGB) in forestlands. Given that this assumption is appropriate, one might be able to minimize budget, time, and labor associated with conventional field measurements for AGB estimation.

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The issue of global warming has received much attention around the world in the last two decades, because of accumulating CO₂ in the atmosphere from combustible fuels and land-use changes. Various scientists and international organizations have warned that the global mean temperature may increase 1.8-3.5°C (Stocks et al., 1998) or 1.4-5.8°C (IPCC, 2001) by the end of the 21st century. Such global temperature increases have the potential to greatly alter global ecosystems (Noss, 2001). Therefore, to maintain the global ecosystem close to present conditions, we need to find globally practicable solutions. On August 31, 2005, 155 nations signed the Kyoto Protocol, a global agreement that aims to cut anthropogenic CO₂ emission levels, at least 5% lower than 1990 levels, by 2008-2012 (UNFCCC, 2005).

Forestlands would play a key role in mitigating global warming from CO₂ increase because forests are a dominant carbon sink among terrestrial ecosystems. The Kyoto Protocol promotes conservation and maintenance of forests, and proposes a new system for dealing with CO₂ reduction, called carbon trading. Under this new system, industries that release CO₂ into the atmosphere must recapture a portion of this emitted carbon through other activities, such as growing forests. Under the Kyoto Protocol, these firms are not required to grow forests themselves, but they must purchase credits related to an equivalent portion of carbon-fixed forest area. The assumption in carbon trading is that industries that find it difficult to regulate or minimize the CO₂ emissions while maintaining or increasing profits, could capture their assigned levels of fixed carbon by purchasing and preserving an equivalent amount of forestland as carbon credits (Jung 2005). However, to put the new system on track, we need a method to easily assess how much biomass is present in forestlands (Murray et al., 2000). One such measure is above-ground biomass (AGB). Various conventional field measurement methods can be used to carry out highly accurate AGB estimation at the stand-level, but it is labor intensive; thus the time and cost requirements are high (Hyde et al., 2006; Lu, 2005). Also, conventional field measurements are not easily performed in remote areas, such as forestlands in mountain ranges. Instead of using field measurements, using a TM image could be used to assess AGB over broad areas quickly, and at a reasonable cost.

Four major advantages of using TM images for the AGB estimation are as follows:

1. Cost of TM image: In 2006, a TM image costs about \$425 from USGS, which is inexpensive relative to other remotely sensed imagery.
2. Coverage of a TM image: A TM image covers an area of 170×185 km (3,145,000 ha), which is far greater than the area captured by conventional aerial photographs using 9×9 inch format film, as well as with most other remote sensors.
3. Temporal resolution: Landsat TM revisits the same area to capture an image every 16 days. This enables frequent assessment of subtle AGB changes, such as those caused by natural disasters. Also, it increases the probability of capturing images under cloud-free condition.
4. Available classification methods: A wide variety of image classification methods for AGB estimation using TM images have been developed over the past three decades. However, most of them are difficult to implement for those who have limited knowledge

of advanced mathematics, image classification techniques, and computer programming languages. Examples of such classification methods are artificial neural networks (e.g. Jensen et al., 1999; Foody et al., 2001; Ingram et al., 2005) and k-nearest neighbor classifications (e.g. Trotter et al., 1997; Holmgren et al., 2000). On the other hand, one simple method, regression analysis, has shown the potential for moderately accurate AGB estimation in various types of forestlands. As a result, regression analysis, one type of supervised classification method, will be implemented in this research. A major advantage in using regression analysis is that it should be the easiest to understand for those who are not experts in image classification techniques, which are available in image processing programs such as ERDAS Imagine (Leica Geosystems Geospatial Imaging, LLC).

Most previous studies for AGB estimation in North American coniferous forestlands resulted in moderately high overall accuracy, as noted using the coefficient of determination (R^2) (e.g. Ahern et al., 1991; Zhang et al., 2004). Lu (2005), using simple linear regression, achieved an R^2 of 0.74 for AGB in the Brazilian Amazon. Steininger (2000), using multiple regression, achieved an R^2 of 0.71 for AGB in the Brazilian Amazon. The AGB estimation accuracy can be relatively lower in tropical rainforests because they are much more diverse in species composition and greater in actual AGB than temperate forestlands (Bastin 1997; Foody et al., 2001; Lu, 2005).

The general objective of this research is to assess the ability to rapidly and accurately estimate AGB at the stand level, using one TM image with regression analysis. The following are the specific objectives of the research.

1. Develop a regression model (AGB estimation model) between spectral reflectance values in the TM image and AGB attained from reference points.
2. Establish a correlation between estimated AGB derived from the regression model and measured AGB attained from test points for the accuracy assessment.
3. Classify the TM image using the regression and correlation results.
4. Evaluate the accuracy of AGB estimation in the multi-species forest.
5. Determine the required number of reference points needed to develop a strong regression model for AGB estimation.
6. Discuss the applicability of using the TM image for AGB estimation at a small forested area.

METHODS

Study Area

The study site for this AGB estimation research is the Whitehall Forest in Clarke County, Georgia (33°52'N and 83°22'W) (Figure 1). The Whitehall Forest has an area of about 300 hectares, and the elevation range above mean sea level is between 160 and 220 m. Mean monthly temperature ranges from 0.6 °C in winter to 32.2 °C in summer. Mean annual precipitation is about 127 cm. The Whitehall Forest was once used for cotton plantations until the 1930s. After that time, the abandonment of old fields resulted in the establishment of natural hardwood and pine stands. Later, some of these areas were cleared and converted to pine

plantations. Since the 1960's, the Warnell School of Forestry and Natural Resources at the University of Georgia has managed this property for teaching, research and outreach purposes.

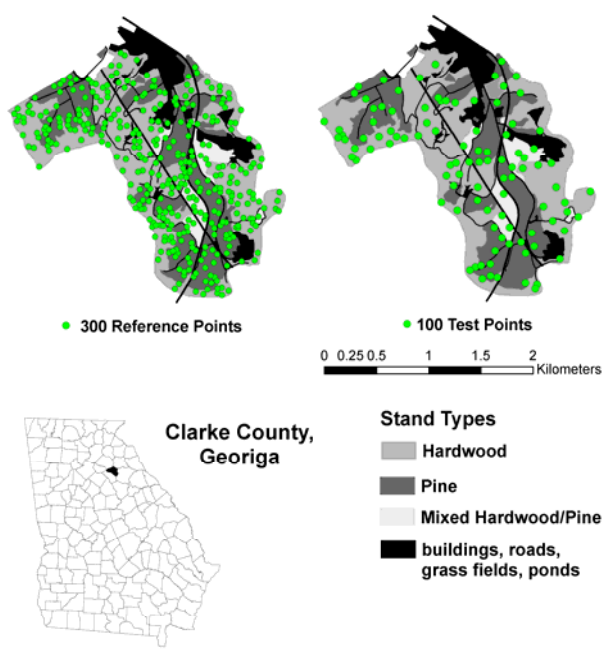


Figure 1. Study area - Whitehall Forest in Clarke County, Georgia.

In 2005, about 70% of the area in the Whitehall Forest was covered with hardwood stands, and 15% and 10% was covered with pine and mixed hardwood/pine (mixed) stands, respectively. The rest of the area is comprised of buildings, roads, ponds and open grass fields. Hardwood stands are composed of various species, dominated by *Quercus rubra* (northern red oak), *Quercus alba* (white oak), *Quercus spp.* (other oak species), *Carya spp.* (hickory species), *Liquidambar styraciflua* (sweetgum), *Liriodendron tulipifera* (yellow-poplar) and *Platanus occidentalis* (sycamore). Pine stands are composed of mainly planted *Pinus taeda* (loblolly pine) and some naturally regenerated *Pinus echinata* (shortleaf pine). Most hardwood stands have reached mature stages from natural regeneration after the abandonment of cotton plantations, but few hardwood stands were planted. Stand age classes among pine stands vary from 10 to 60 years. Stand age classes among mixed stands range from 20 to 40 years. Periodically, some forest stands are subjected to prescribed fire to control fuel loads, and to provide educational experience for natural resource students.

Field Measurement

AGB will be estimated on 400 randomly located reference points in the Whitehall Forest (Figure 1). Trees around each point are sampled using a BAF 10 prism. Per-0.09 hectares (30×30 m) estimates of tree structure will be developed for each reference point. The location of each reference point will be determined using a GPS unit (Trimble GeoExplorer3) without the onsite differential correction. AGB in each reference point will be derived using the tree structure data

in conjunction with published allometric equations (e.g. Clark et al., 1986; Birdsey, 1992; Smith et al., 2004; Williams and Gresham, 2006).

Image Classification – Regression Analysis

The spectral reflectance values for areas represented by each reference point will be extracted from a sub-scene (e.g. TM band 3 image) of the TM image using ERDAS Imagine. The spectral reflectance values and the AGB measured at the reference points will be used to develop the regression model. The spectral reflectance and other vegetation indices, such as normalized difference vegetation index (NDVI) will be the independent variables, and AGB from the reference points will be the dependent variable. Once a regression model with good predictive ability is developed, AGB for the entire area will be predicted.

Accuracy Assessment

Accuracy of the AGB estimation will be assessed using reference points that are not included in the development of the regression model. Those points are set as test points. The accuracy level of the developed regression model will be assessed by the coefficient of determination (R^2). Higher values of R^2 correspond to closer correlation between the estimated AGB from the developed regression model and measured AGB from test points. The correlation may be explained as linearly, curvilinearly, or logistically.

RESULTS AND DISCUSSION

Analyses are currently ongoing. We expect to construct a relatively strong regression model between spectral reflectance values in TM bands 1-5 and 7, and AGB measured at reference points. While about 70% of our study site is occupied by temperate hardwood species, the accuracy level in AGB estimation for this forestland should be predicted at least at same level of accuracy in the studies of Brazilian Amazon (e.g. Steininger, 2000; Lu, 2005), due to less complex stand structures in the Whitehall Forest. However, since few studies have focused on AGB estimation for such a small forestland, the applicability of the TM image with regression analysis is uncertain at this point.

Additionally, to determine the minimum number of reference points required, 300 randomly chosen field plots will be measured for developing regression models, and 100 randomly chosen points as test points will be used for the model validation. Several regression models will be developed from different sets of reference points. The R^2 of four models based on 50, 100, 200 and 300 reference points will ultimately be compared, and hopefully some insight into the amount of reference points necessary to moderately accurately estimate AGB will be gained.

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