ABOVE GROUND BIOMASS ESTIMATION IN A 285-HECTARE SITE OF MIXED PINE-HARDWOOD USING LANDSAT THEMATIC MAPPER IMAGERY AND REGRESSION ANALYSIS

by

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(Under the Direction of Pete Bettinger)

ABSTRACT

The objective of this study was to assess the applicability of using TM imagery for estimating above ground biomass (AGB) in a small forestland. Based on a single Landsat TM image, spectral reflectance from six TM bands and three vegetation indices was correlated to ground-based AGB measurements using regression analysis to develop AGB models. The fit of models was evaluated using the coefficient of determination (R^2). An accuracy assessment using independent test points was performed for the best model. Overall this study found that lower numbers of training points resulted in higher R^2; however, models with high R^2 did not show high accuracy levels when validated against an independent sample of data. Predicted values for AGB models were consistent among models that modeled: all tree species; all tree species in interior forest stands; hardwood stands; or pine stands.

INDEX WORDS: Landsat TM, above ground biomass, regression analysis, training points, regression models, remote sensing, Kyoto Protocol, carbon budget trading

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TABLE OF CONTENTS

Page

ACKNOWLEDGEMENTS iv

LIST OF TABLES ix

LIST OF FIGURES xi

CHAPTER

1 INTRODUCTION 1

1.1 Global warming, carbon budget trading and remote sensing 1

1.2 Five major advantages of using Landsat TM imagery for AGB estimation 3

1.3 Four ambiguous factors associated with TM imagery for AGB estimation 5

2 Literature review 9

2.1 Overview of AGB estimation using Landsat TM imagery 9

2.2 Five issues regarding three image classification methods 10

2.3 Three widely used image classification methods 13

3 Purpose of the study 19

3.1 Summary 19

3.2 Objectives 19

4 Methods

4.1 Study area 21

4.2 Training and test points 23

4.3 Field measurement – Estimation of actual AGB in training and test points 25

4.4 Satellite image data 28

4.5 Accuracy assessment.. 32

5 Results...33

5.1 Overall summary 34

5.2 Development and assessment of regression modes for the entire study site.....35

5.3 Development and assessment of regression modes for the interior forest stands..38

5.4 Development and assessment of regression modes for the hardwood stands..41

5.5 Development and assessment of regression modes for the pine stands 44

5.6 Different sets of test points for the accuracy assessment 47

5.7 Accuracy assessment using error matrix 49

6 Discussion...52

6.1 The relationship between numbers of training points and model R^2 values 52

6.2 The relationship between model R^2 values and accuracy levels 53

6.3 Impact of normality of independent variables and effective vegetation indices...54

6.4 Impact of uncertainty of field points on development of regression models 55

6.5 Impact of stand edges on development of regression models 56

6.6 Effect of mixed-species stands on development of regression models 56

6.7 Applicability of basal area and height estimations..57

6.8 Contribution for future study...57

7 Conclusion 59

REFERENCES 62

APPENDICES 66

A Models were developed using a bootstrapping technique to draw a small set of training point from a larger sets of potential training points 66

B The best combination of independent variables for above ground biomass (AGB), basal area, and height estimation based on Akaike's Information Criterion (AIC) ...72

C The normality test in independent variables based on Kolmogrov-Smirnov test values...78

LIST OF TABLES

Page

Table 1: The spectral resolution of Landsat TM 5 image 4

Table 2: Number of training points used to develop regression models and number of test points used to assess developed models 24

Table 3: Volumes (wood only) of major species found in the study area 27

Table 4: Coefficient of determination (R^2) between nine independent variables and actual AGB, basal area, and height based on (a) thirty, (b) fifty, (c) one hundred, and (d) two hundred training points 36

Table 5: The accuracy assessment of developed regression estimation models for the study site 38

Table 6: Coefficient of determination (R2) between nine independent variables and actual AGB, basal area, and height based on (a) thirty, (b) fifty, and (c) one hundred training points in the interior forest stands 40

Table 7: The accuracy assessment of developed regression estimation models for the interior forest stands 41

Table 8: Coefficient of determination (R2) between nine independent variables and actual AGB, basal area, and height based on (a) thirty, and (b) fifty training points in the hardwood stands 43

Table 9: The accuracy assessment of developed regression estimation models for the interior hardwood stands 44

Table 10: Coefficient of determination (R2) between nine independent variables and actual AGB, basal area, and height based on (a) thirty, and (b) fifty training points in the pine stands 45

Table 11: The accuracy assessment of developed regression estimation models for the interior pine stands 46

Table 12: Coefficients and an intercept of each best predictive model for AGB, basal area, and height estimations for (a) the entire study site, (b) the interior forest stands, (c) the hardwood stands, and (d) the pine stands..47

Table 13: The accuracy assessment for AGB estimation in the entire study site 48

Table 14: The accuracy assessment using error matrix for (a) the entire study site, (b) the interior forest stands, (c) the hardwood stands, and (d) the pine stands 50

LIST OF FIGURES

Page

Figure 1: Location of the Whitehall Forest (size 285 ha) with stand map in Clarke County, Georgia 22

Figure 2: 380 randomly located points (300 training and 80 test points) in the study site 23

Figure 3: Two Landsat TM 5 images present the Whitehall Forest 28

Figure 4: A hypothetical example of the strict pixel-based (SPB) approach 30

Figure 5: A hypothetical example of the inversely weighted Euclidean distance (IWED) approach 30

CHAPTER 1

Introduction

1.1 Global warming, carbon budget trading and remote sensing

Since the beginning of the Landsat Project, led by mainly NASA and the U.S. Geological Survey (USGS) in 1972, numerous types of satellite imagery have been available for public use. Various researchers in different areas of research have developed techniques to classify ground features in remotely sensed images, such as those captured by a Landsat Thematic Mapper 5 (TM). Results of this work have made it possible to efficiently produce land cover/type maps at broad spatial scales. Given that satellite imagery has been used to classify vegetation, it is not unreasonable to expect that TM imagery could be used to estimate above ground biomass (AGB) in forestland even though AGB is measured on a continuous scale, whereas vegetation is usually limited to a small set of discrete classes. If so, substantial cost savings could be gained in terms of time, and labor associated with conventional field measurements for AGB estimation.

Global warming has received much attention around the world for decades. Because of accumulating CO_2 in the atmosphere from combustible fuels and land-use changes as well as the subsequent loss of forests to sequestrate carbon, various scientists and international organizations have warned that the global mean temperature may increase 1.4-5.8°C by the end of the 21st century (IPCC 2001). Mote *et al.* (2003) predicted temperature increases of 1.5-3.2°C in the Pacific Northwest by the 2040s, which would result in below average salmon survival and tree growth in the region. Logan *et al.* (2003) warned that there is a great possibility of insect and pathogen outbreaks in forestland due to global warming. Furthermore, Walther *et al.* (2002) warned that global warming would, particularly, influence ecosystems in the northern hemisphere regarding phenological cycles, exotic species invasions and community shifts. Therefore, to maintain global ecosystems close to present conditions, we need to find globally practical solutions to mitigate CO_2 concentration in the atmosphere. This is the reason that on August 31, 2005, 155 nations ratified the Kyoto Protocol, a global agreement that aims to cut anthropogenic CO_2 emission levels to at least 5% lower than 1990 levels by 2008-2012 (UNFCC 2005).

Various scientists have tried to determine the causes and mechanisms of global warming. Unfortunately, they have not found a definititive answer yet, but most scientists have agreed that global warming has occurred, and CO_2 accumulation in the atmosphere is the major cause (Litynski *et al.* 2006). Excess CO_2 accumulation comes primarily from anthropogenic activities, such as the combustion of fossil fuels, land use change and deforestation (Litynski *et al.* 2006). To mitigate global warming from CO_2 buildup in the atmosphere, forests could play a key role because they fix CO_2 gas into tree structures as a solid carbon form; thus, forests could be a dominant carbon sink among terrestrial ecosystems. The Kyoto Protocol promotes conservation and maintenance of forests, and proposes a new system for dealing with CO_2 reduction called carbon budget trading. Under this new system, industries that release CO_2 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 if not they must purchase an equivalent portion of carbon-fixed forest area. The assumption in carbon budget trading is that industries that find it difficult to regulate or minimize CO_2 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). To implement the new method, however, a method is needed to easily assess how much biomass is present in forests, especially as above ground biomass (AGB) in the form of tons carbon (ton-c).

Various conventional field measurement methods can be used to carry out accurate AGB estimation at the stand-level, but because of labor, costs and time considerations, it is difficult to scale up such analyses beyond the stand-level. Also, analyses are likely to require additional visits to verify AGB at later times. Additionally, conventional field measurements are not easily done in remote areas, such as forestlands in roadless areas or mountain ranges. The goal of this study was to evaluate the applicability of a new method capable of rapidly and accurately estimating AGB at stand to landscape extents, using readily available remotely sensed imagery, such as Landsat TM, as well as readily available AGB estimation method for a small to medium sized landowner. A secondary goal was to determine how many training points were necessary to obtain reasonablely high accuracy estimate of AGB.

1.2 Five major advantages of using Landsat TM imagery for AGB estimation

<u>Advantage 1 - cost of TM image</u>

In 2006, the year of this study, one TM image cost about $425 (USGS 2006), which was inexpensive relative to other remotely sensed images (Lefsky *et al.* 2001). For example, IKONOS images, which were made available beginning in 2000, offer higher spatial resolution than Landsat TM. However, the price of the images is much more expensive, ranging from $2,000 to $4,000 for an image covering only a small portion of a TM image.

Advantage 2 - coverage size

One TM image covers an area of 170×185 km (3,145,000 ha), which is greater than the area captured by traditional aerial photographs (using a 9×9 inch format), as well as other remotely sensed images (Ahern *et al.* 1991, Lefsky *et al.* 2001). Also, Landsat TM provides worldwide coverage. Some remote sensing services, such as IKONOS, capture images in limited areas.

Advantage 3 - spectral range

Landsat TM is equipped with a multispectral sensor to sense a wide range of spectral information reflected from objects on the Earth. The multispectral sensor is composed of seven different spectral ranges, called TM bands 1-7, basically covering the visible light region to a thermal infrared region. The spectral resolutions of TM bands are listed in Table 1. Some other satellite sensors, such as IKONOS, do not cover such wide range of spectral resolutions.

Table 1. The spectral resolution of Landsat TM 5 image

TM Band	Spectral Sensitivity (µm)	Spectral Region
1	0.45 - 0.52	Blue
2	0.52 - 0.60	Green
3	0.63 - 0.69	Red
4	0.76 - 0.90	Near infrared
5	1.55 - 1.75	Mid infrared
6	10.40 - 12.5	Thermal
7	2.08 - 2.35	Mid infrared

Advantage 4 - temporal resolution

Landsat TM re-visits the same area to capture an image every 16 days. This enables frequent assessment of subtle land cover and biomass changes, such as those caused by natural disasters (Ahern *et al.* 1991). One must, however, determine whether images acquired on cloud-free days were available over this time interval; thus, repeatability may not necessary be 16 days.

Advantage 5 - available AGB estimation methods

Researchers have developed a wide variety of image classification methods as well as AGB estimation methods, in conjunction with TM images over the last three decades. While certain AGB estimation methods are difficult to implement for workers without advanced mathematical and computer skills (Foody *et al*. 2001), one simple method, regression analysis, is available and has potential for fairly accurate AGB estimation in various forestland types at the landscape level.

1.3 Four ambiguous factors associated with Landsat TM imagery for AGB estimation

For accurate AGB estimation, one needs to examine and overcome four ambiguous factors associated with TM images.

Ambiguous factor 1 - mixed pixel problems

The pixel (or ground) resolution of TM images may not be sufficient for moderately accurate (R^2 of 0.6-0.8) AGB estimation with respect to carbon budget trading. The pixel resolution is 30×30 m (0.09 ha), which makes “mixed pixels” an issue. For instance, if an area of 30×30 meters in a forest stand is occupied by maple (60%) and oak (40%), the pixel in the image may show the reflectance value of only maple, and perhaps the oak reflectance would be ignored if the oak is dominant only in the understory. In fact, the pixel reflectance value might represent an entirely different species than either maple or oak, if both are dominant in the overstory. Thus, it may be difficult to estimate AGB at different points in the objective area due to pixel resolution. However, the high pixel resolution of an IKONOS image, providing a 4×4 m pixel resolution, also may not be appropriate because it would capture too much of natural variation caused by sun angle, topography, different crown shapes among the same species, natural breaks in the canopy, as well as other abiotic and biotic factors. This heterogeneity in spectral reflectance would make estimating AGB problematic using very high pixel resolution imagery (e.g., < 10 m pixel sizes).

Ambiguous factor 2 - stand parameters for AGB estimation

It is difficult to assess valuable stand parameters for AGB estimation from TM images. Generally, AGB is estimated through an allometric equation with stand parameters, such as stem diameter, tree height, stand age, or leaf area index acquired from field measurements. However, to acquire such stand parameters using the ground resolution of 30×30 m represented by TM image pixels presents a problem. It is almost impossible to acquire individual stem diameter and height due to the pixel resolution. To address this problem, a simplifying assumption must be made: a level of crown closure which can be reliably measured using TM images (Fassnacht *et al*. 1997, Eklundh *et al.* 2001, Eriksson *et al.* 2006) corresponding to a spectral reflectance value in a pixel is assumed to indirectly correlate to average stem diameter and height in a 30×30 m field point. In this manner, AGB can be estimated based on a TM image.

Ambiguous factor 3 - sizes of objective areas for AGB estimation

Few previous studies for AGB estimation from TM images have been implemented on forestlands smaller than 5,000 hectares. A reason might relate to the locational error between a pixel in a TM image and a field point (Hall *et al.* 2006, Labrecque *et al*. 2006). First, delineating and orienting a square field plot in the field is difficult, and second, ensuring that it physically matches a satellite image pixel is impossible. Such locational error would exist when sizes of objective areas are smaller. However, this study is concerned with the process by which a small to medium sized landowner might successfully employ to estimate AGB.

Ambiguous factor 4 - required training and test AGB data for AGB estimation

A major problem for AGB estimation based on TM imagery is that the accuracy of predicted AGB will depend on the number of training points derived from field measurements used to build the regression equations. Few previous studies for AGB estimation using TM images have assessed the minimum required number of training points require to achieve a desired level of accuracy. Furthermore, for a validation or accuracy assessment of regression AGB estimation models, independent field measurements are needed. Some previous studies (*e.g.* Steininger 2000) did not validate their models with additional field data.

Therefore, this thesis assessed the applicability of a Landsat TM image for AGB estimation in a small forested site. First, this research focused on the development of the relationship between spectral reflectance values from a Landsat TM image and field measured AGB from conventional field measurement using regression analysis. The fit of developed models to the observed field data was assessed using the coefficient of determination (R^2)

between estimated AGB and field measured AGB. Second, while few previous studies have intensively examined the relationship between required numbers of training points in the development of regression models, this research investigated how many training points are needed to derive a certain accuracy level in AGB estimation using a single Landsat TM image.

CHAPTER 2

Literature review

2.1 Overview of AGB estimation using Landsat TM imagery

Since the beginning of Landsat project in 1972, research has been conducted to examine various methods aimed at estimating AGB in various types of forestlands (*e.g*. Ripple *et al*. 1991, Holmgren *et al*. 2000, Lu *et al.* 2004). Examples of widely used AGB estimation methods include artificial neural networks, k-nearest neighbors, and regression analysis. Each of these will be addressed shortly. Regression models that use spectral reflectance values from TM imagery and field measured AGB from training points are often evaluated using the coefficient of determination (R^2), adjusted coefficient of determination (R^2_{adj}), coefficient of correlation (r), the root square mean error (RSME), or standard error (SE). Higher values of R^2, R^2_{adj} and r, and smaller values of RSME and SE indicate better estimation models or a tighter fit to the observed data. Models need to be validated using independently field measured AGB from test points. However, a limited number of previous studies assessed their models in this manner (*e.g.* Foody *et al.* .2001, Ingram *et al*. 2005, but see Franklin 1986, Ahern *et al*. 1991, Steininger 2000). A major reason was that it was difficult to collect additional field data, as a test dataset, for assessment purposes.

2.2 Five issues regarding three image AGB estimation methods

There are five issues associated with the three widely used AGB estimation methods. The first relates to the optimal area required to derive accurate results of AGB estimates. Although a number of previous studies did not report the size of the study areas, a majority of previous AGB estimation studies focused on areas greater than 5,000 ha. Ahern *et al.* (1991) suggested that one should be able to derive reliable forest parameters, such as AGB, in areas greater than 100,000 ha using remotely sensed imagery. AGB estimation would be more accurate in larger areas than smaller areas using a TM image, because some noise or errors in spectral reflectance values would be mitigated by surrounding pixels after applying a moving window approach to smoothing the data.

The second issue relates to how many training data are necessary to derive strong predictive regression models. Some previous studies used a large number of training plots, like the U.S. Forest Service's Forest Inventory and Analysis (FIA) data (*e.g.* Holmgren *et al*. 2000, Reese *et al*. 2002), but a majority of developed estimation models were based on less than 100 training plots.

The third issue is that one may not be able to estimate AGB using TM imagery. A TM image contains spectral reflectance values associated only with the material present in uppermost layer (e.g., vegetation's canopy or crown structure), whereas AGB includes the entire structure of a forest including understory canopy and shrub layers. Some previous studies reported that spectral reflectance values and leaf area index (LAI), particularly in hardwood stands, were correlated (Ahern *et al*. 1991, Steinger 2000, Lu *et al.* 2004). Thus, canopy structure, as a forest parameter, may indirectly relate to AGB. For example, one assumption is that larger canopy trees would contain greater biomass. However, a problem is that a TM image may not clearly represent some aspects of canopy structure, such as crown height. Canopy structures in older stands tend to have increased number of shadows, which means decreasing spectral reflectance values in certain band ranges, such as bands 5 and 7. Contrarily, canopy structures in younger stands tend to increase spectral reflectance values in bands 5 and 7. In addition, stand conditions, such as closed canopy or open canopy stands, influence spectral reflectance values in TM bands. Spectral reflectance values in open canopy stands would contain a mixture of reflectance values from understory and overstory vegetation, as well as the soil. This problem is inherent in the three widely used AGB estimation methods.

The forth issue is that it is difficult to accurately locate training points and test points in a study site exactly to a single pixel in a TM image. While locations of training and test points are usually determined by GPS in the study site, GPS points have positional errors, which normally range from 3 to 15 m, depending on the conditions of overstory vegetation, topography, and satellite geometry. Also, it is almost impossible to locate precisely each training and test point on the center of 30 m grid of Landsat pixels. To accommodate this locational problem, some researchers have used a moving window, such as a 3×3 window (*e.g.* Salvador and Pons 1998, Foody *et al.* 2001, Makela and Pekkarinen 2001, Lu *et al.* 2004, Labrecque *et al.* 2006). A moving window averages the spectral reflectance values in surrounding pixels; thus, in the case of the 3×3 window, the spectral reflectance values of nine pixels are averaged. A majority of the articles has reported that the 3×3 moving window approach resulted in the development of stronger AGB estimation models than a strict pixel-based (SPB) approach of using the single pixel that matched the single field point (Hall *et al*. 2006, Labrecque *et al*. 2006). The study site in this study was a small forest of about 300 ha, and a number of the pixels fall on edges of stands between vegetated and non-vegetated areas. Thus, a moving window would not be suitable because the average spectral reflectance value likely contains non-vegetated spectral reflectances. Instead of performing a moving window, this study performed an inversely weighted Euclidean distance (IWED) approach, and results of developed AGB estimation models were compared to results based on a SPB approach. The IWED approach averages spectral reflectance values in four closest pixels from each training point (including the single pixel the point falls in), and those four spectral reflectance values are inversely weighted based on Euclidean distances between each training point and the centers of four closest pixels. This approach is somewhat similar to a moving window, but because of the small geographic extent of the study area, the IWED approach should be more appropriate.

Finally, a wide rage of literature has reported that using values from vegetation indices (assigned to each pixel) would be superior to using values straight from the TM bands (*e.g.* Foody *et al*. 2001, Mallinis *et al.* 2004, Freitas *et al.* 2005, Ingram *et al*. 2005). Using vegetation indices can maximize the sensitivity for capturing the abundance and condition of green vegetation. Vegetation indices may minimize the effects of sun angles, topography, and atmospheric variability. However, because various combinations of TM bands 1-5 and 7 are used to develop a majority of the vegetation indices, information in other TM bands is not used, even though it could contribute to the development of a stronger predictive model (Foody *et al.* 2001). For example, the most widely used vegetation index, the normalized difference vegetation index (NDVI), uses only TM bands 3 and 4. This thesis selected and examined three vegetation indices to determine whether they could improve the accuracy of AGB estimation, compared with spectral reflectance values in the original TM bands.

2.3 Three widely used AGB estimation methods

Artificial Neural Networks

Foody *et al.* (2001) developed three types of artificial neural networks to estimate biomass in the Bornean tropical rainforest. In this study, twenty training plots were used to develop the estimation model, and ten test plots were used to assess actual and estimated biomass. One of the artificial neural networks developed had a strong predictive model (R^2 = 0.8033). Foody *et al.* (2003) also developed an artificial neural network to estimate AGB in the Brazilian, Thai and Malaysian tropical rainforests. They developed a fair estimation model with an R^2 of 0.505 for the Thailand study. The prediction accuracy of this model between actual and estimated AGB was R^2 of 0.411, but the article did not report how many test plots were used for this assessment.

Ingram *et al.* (2005) developed an artificial neural network to estimate basal area, as a related parameter to AGB, in the southern Madagascar tropical rainforest. They developed a fair estimation model of $r = 0.82$. Fifteen training plots were used for model development and sixteen test plots were used to estimate accuracy ($r = 0.69$).

These three studies using artificial neural networks were also compared with regression analysis techniques. The conclusions were generally that artificial neural networks should be superior to regression analysis. However, one issue in the study was the limited number of training and test plots compared to what has been used in other similar studies to evaluate the applicability of artificial neural networks (Foody *et al.* 2001). In addition, the size of their study sites was not reported. Further, the development of artificial neural networks would require advanced programming skills, and it is difficult to understand the behavior of an internal process within an artificial neural network from simply examining input and output data (Foody, *et al.*

2001). Since this project was aimed at a method that a small lot landowner could employ, we chose not to pursue this method.

k-Nearest Neighbors (*k*NN)

Holmgren *et al.* (2000) developed a *k*NN approach to estimate stem volume in 19 ha stands in the western Sweden. Based on only spectral information in TM bands, they developed an estimation model, which arrived at standard error (SE) of 36%. Two hundred ninety-six training plots from the National Forest Inventory were used in this model development. Also, besides spectral information in the TM image, Holmgren *et al.* (2000) reported that SE decreased once additional ancillary information, such as site index, stand age, or tree height was integrated within the *k*NN technique.

Reese *et al.* (2002) developed a *k*NN approach to estimate timber volume at five different locations in Sweden. They developed estimation models, which had a RMSE between 59% and 80% for mean wood volume. These models were developed based on a strict pixel-based approach. National Forest Inventory data were used for the training and test data, but the number of training data for estimation models and the assessment for those models were not reported. Aggregations of smaller stands to set larger spatial areas decreased RMSE about 20% for 50 ha, and about 10% for 100 ha.

Labrecque *et al.* (2006) developed three types of *k*NN techniques to estimate biomass in western Newfoundland. The developed estimation models had a RMSE of about 37-81 tons per ha. One hundred sixty-nine training plots were used for the model development, and they were assessed based on two hundred seventy-six test plots. About 85% of the study sites consisted of conifer stands. Also, the article reported that RMSEs were lower than biomass estimates developed through regression analysis techniques.

One issue in using *k*NN techniques for AGB estimation is that users need to arbitrarily decide the optimal number of *k*, which depends on training and other ancillary data, and the target level of accuracy (Reese *et al.* 2002). In addition, *k*NN tends to overestimate forest parameters, such as timber volume, in low volume stands, and underestimate these in high volume stands (Fazakas *et al.* 1999, Holmgren *et al.* 2000, Reese *et al.* 2002). In addition, a majority of previous studies performing *k*NN to estimate forest parameters were done for conifer-dominated forestlands, such as boreal forests and plantation forestlands. Thus, the applicability of *k*NN in hardwood-dominated forestlands has not been determined. Finally, a majority of previous studies used various government-level forest inventory data as training and test data. While such type of inventory data may cover larger spatial areas, it may not represent conditions of forestlands at spatial extents smaller than 510 ha (Fazakas *et al.* 1999) since the plots are generally spaced tens of thousands of km apart. Consequently, *k*NN techniques may not be suitable to apply small forestland areas.

Regression analysis

Franklin (1986) performed regression analysis to estimate basal area in stands in the Mendocino National Forest, California. This study used an airborne thematic mapper simulator, which has a similar sensor characteristic to TM spectral bands, but the pixel resolution was not reported. A developed estimation model had an R^2 of 0.54 between band 3 and actual basal area from nineteen training plots, but this model was not assessed using independent test plots. Importantly, the article reported that spectral reflectance values in TM bands may be more strongly affected by stand structure and density, rather than species composition in conifer-dominated forestland.

Ahern *et al.* (1991) performed regression analysis to estimate *Picea spp.* and *Abies spp.* (spruce-fir) volume in the northwestern New Brunswick. A developed regression model had an R^2 of 0.808 between band 4 and actual volume. The relationship indicated that spectral reflectance values in band 4 were higher in low volume spruce-fir stands, and lower in high volume stands due to the influence of hardwood adjacent to spruce-fir. However, this estimation model was not assessed using independent test plots. Also, the article did not report the number of training plots used to develop the regression model.

Steininger (2000) performed regression analysis to estimate AGB in tropical secondary forests at Brazil and Bolivia. In the Brazilian study site, the best estimation model had an r (coefficient of correlation) of 0.715, between band 5 and actual AGB from 18 training plots. A multiple regression analysis using bands 3, 4 and 5 barely improved on this. Contrarily, in the Bolivian study site, a strong predictive regression AGB estimation model could not be developed. In the Brazilian study site, there was a strong correlation between crown structure and tree height, and AGB. In other words, taller trees with larger crowns resulted in greater AGB, but in the Bolivian study site, such relationship was weak. The article reported that band 5 was the most useful for AGB estimation. However, this study did not assess the estimation model using independent test plots.

Lefsky *et al.* (2001) performed regression analysis to estimate AGB and other forest parameters, such as mean DBH, in the *Pseudotsuga menziesii* (Douglas-fir) dominated forestland of western Oregon. This study used two different types of TM imagery, one was used a single TM image, and the other was a TM mosaic that was built to combine six TM images, representing six different months of a year. Based on the single TM image, the best estimation model had an R^2_{adj} of 0.31, and based on the TM mosaic, the best estimation model had an R^2_{adj} of 0.60. Both models were developed using ninety-two training plots. Although the TM mosaic resulted in the development of a better predictive model than the single TM image, only two out of the six TM bands largely contributed such improvement. Thus, the multitemporal mosaic approach may result in an unnecessary cost of extra images. Additionally, both models were not assessed using independent test plots.

Mallinis *et al.* (2004) performed regression analysis to estimate biomass in north-central Greece. The best estimation model, but not statistically significant at the 0.05 level, had an R^2_{adj} of 0.066 based on thirty-four training plots and band 4 of the TM imagery. Two vegetation indices, the perpendicular vegetation index and the second principal component, improved predictive powers to R^2_{adj} of 0.159 and 0.170, respectively, with statistical significant at the 0.01 level. Such a low R^2_{adj} was probably due to abruptly fragmented forestlands. Stand structure, such as density, species composition, AGB or other parameters, was not consistently estimated over the study area. Thus, a strong relationship between spectral information in TM bands and AGB may not have been developed.

Freitas *et al.* (2005) performed regression analysis to estimate basal area and mean height in stands in southeastern Brazil. The study area was about 577 ha in size. Instead of using spectral reflectance values in each TM band, values in three different vegetation indices were used to develop regression models. Three vegetation indices were normalized difference vegetation index (NDVI), moisture vegetation index using band 5 (MVI5), and moisture vegetation index using band 7 (MVI7). They arrived at an R^2 of 0.898 for basal area estimation using values only in MVI5. Also, they arrived at an R^2 of 0.882 for mean height estimation using values in MVI5 and MVI7 as a multiple regression model.

Lu *et al.* (2005) performed regression analysis to estimate AGB in the Brazilian Amazon. The best AGB estimation model of a study site had an R^2 of 0.826 between band 5 and actual AGB from fourteen training plots. Also, some vegetation indices were strongly correlated with actual AGB. The tasseled cap transform 1 arrived at an R^2 of 0.835. However, AGB estimation models of one of the study sites did not result in high R^2 between TM bands and vegetation indices, and actual AGB. While training plots in this site showed different amounts of AGB, height distributions were similar among plots. Thus, the literature concluded that it is difficult to develop strong predictive models for complex structure stands. However, the developed models were not assessed using independent test plots.

The primarily finding is previous studies did not report what geographic scales of forestlands would be suitable to use a Landsat TM image based AGB estimation. Also, some studies resulted in the development of high R^2 models based on smaller number of training points, but some other studies resulted in the development of low R^2 models based on greater number of training points. At last, most previous studies did not assess accuracy levels of developed regression models. Without model assessments, applicability of regression analysis is unknown. Therefore, these three factors were investigated in this thesis (see Chapter 3).

CHAPTER 3

Purpose of the study

3.1 Summary

A major advantage in using regression analysis is that it should be the easiest to understand for people who are not experts in AGB estimation techniques. The method is available in GIS programs such as ERDAS Imagine (Leica Geosystems Geospatial Imaging, LLC) and ArcGIS (ESRI). In this study we used regression analysis techniques for AGB estimation, relating spectral reflectance values in TM bands 1-5 and 7, and actual AGB from training points. While about 65% of our study site is occupied by temperate hardwood species, the accuracy level in AGB estimation for this forestland should be similar to those found in the Brazilian Amazon (*e.g.* Steininger 2000, Lu 2005), due to less complex stand structures in the study site chosen (Whitehall Forest, see Chapter 3 for a description of the study site). However, since few studies have focused on AGB estimation for such a small forestland, the applicability of using TM imagery with regression analysis was uncertain at the beginning of this study.

3.2 Objectives

The general objective of this research was to assess the applicability of using TM imagery for estimating AGB of a small forestland. The following are the specific objectives of the research.

1. Develop a regression model using spectral reflectance values in the TM image and field measured AGB from training points
2. Develop a regression model between spectral reflectance values in the TM image and basal area and mean tree height derived from training points
3. Assess the accuracy of the developed regression models against field measured AGB from independent test points
4. Determine the required number of training points needed to develop a strong predictive model for AGB estimation in small areas
5. Discuss the applicability of using TM imagery for AGB estimation on small forestlands

CHAPTER 4

Methods

4.1 Study area

The study site for this AGB estimation study was the Whitehall Forest in Clarke County, Georgia (33º52'N and 83º22'W) (Figure 1). The Whitehall Forest has an area of about 285 ha, and the elevation ranges between 160 and 220 m above sea level. Mean monthly temperatures range from 0.6 ºC in winter to 32.2 ºC in summer. Annual mean precipitation is about 127 cm. A large portion of 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.

In 2006, about 65% of the Whitehall Forest was covered with hardwood stands, and 12% and 8% was covered with pine and mixed hardwood/pine (mixed) stands, respectively. The rest of the area is composed of buildings, roads, ponds and open grass fields. Hardwood stands are composed of various species, the majority being *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 a 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 while most hardwood stand ages are similar. Periodically, some forest stands are burned to control fuel loads, and to provide an educational experience for natural resource students.

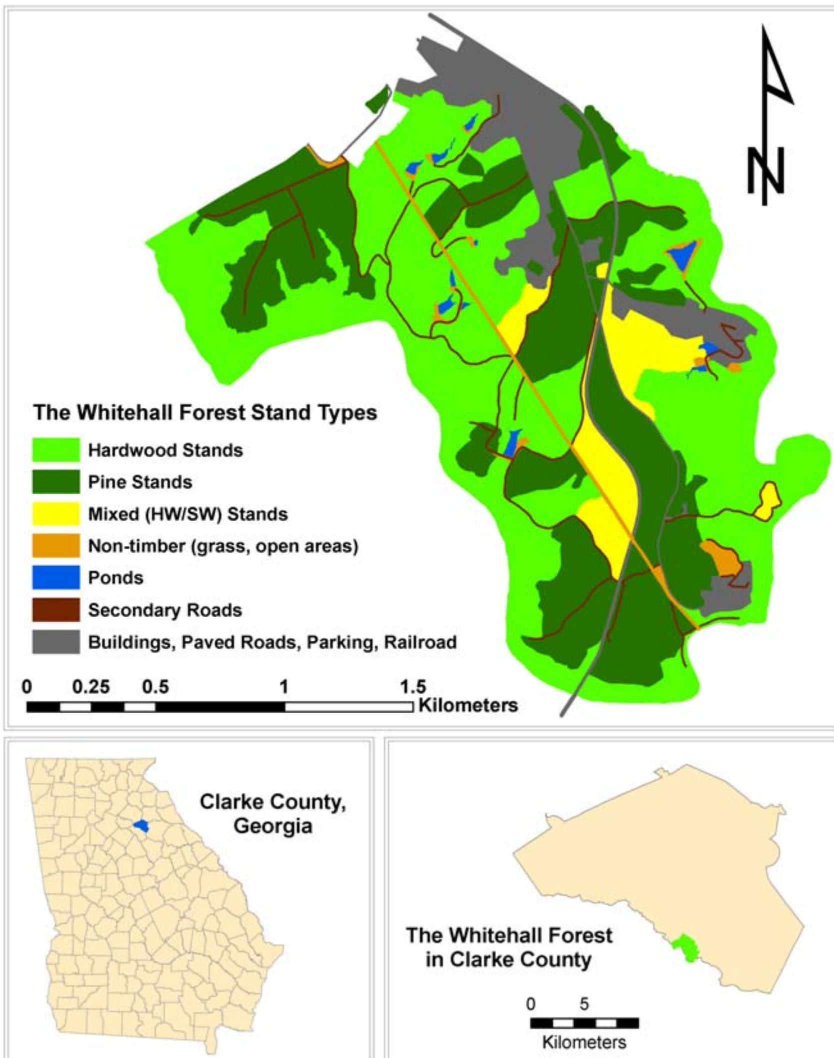


Figure 1. Location of the Whitehall Forest (size 285 ha) with stand map in Clarke County, Georgia

4.2 Training and test points

<u>AGB and forest parameter estimation models for the entire study site</u>

In the Whitehall Forest, a total of three hundred eighty randomly located points were assigned (Figure 2) (Table 2) using a random process. Three hundred randomly drawn points were used as training points, and remaining eighty points were retained for test points. Of the three hundred training points, two hundred, one hundred, fifty, and thirty randomly drawn points were assigned as sets of training points for the development of AGB (total AGB per tons-c per 0.09 ha) and forest parameter (total basal area in cm^2 per 0.09 ha and mean total tree height per 0.09 ha) estimation models. Thus, four regression models were developed based on four different sets of training points. Also, among the eighty test points, fifty randomly drawn points were used as independent test points for model assessment.

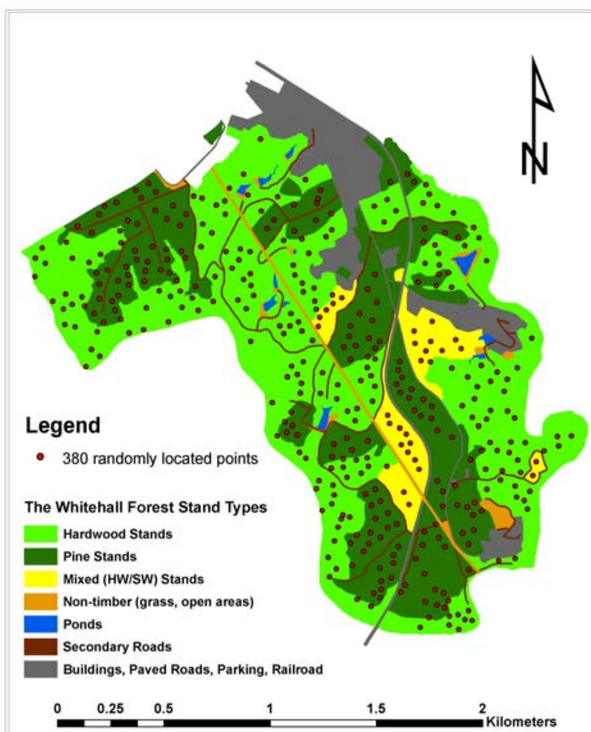


Figure 2. 380 randomly located points (300 training and 80 test points) in the study site

Table 2. Number of training points used to develop regression models and number of test points used to assess developed models.

AGB Model	Total field points	Numbers of potential training points	Numbers of used training points	Numbers of potential test points	Numbers of used test points
The entire study site (four regression models)	380	300	200 100 50 30	80	50 50 50 50
Interior forest stands (three regression models)	263	200	100 50 30	63	50 50 50
Interior hardwood stands (two regression models)	122	92	50 30	30	30 30
Interior pine stands (two regression models	111	81	50 30	30	30 30

<u>AGB and forest parameter estimation models for the interior forest stands</u>

To examine the impact of training points located closer to stand edges, such as edges to other species (hardwood *vs.* pine stands), and training points located near non-timber areas, two hundred sixty-three randomly located points, which were at least 30 m away from stand edges, were selected (Table 2). Two hundred randomly drawn points were used as training points, and remaining sixty-three points were retained as test points. Of the two hundred training points, one hundred, fifty, and thirty randomly drawn points were assigned as sets of training points for the development of AGB and forest parameter estimation models. Thus, three regression models were developed based on three different sets of training points. Also, among the sixty-three test points, fifty randomly drawn points were used as independent test points for model assessment.

AGB and forest parameter estimation models for the interior hardwood stands

To examine the impact of multiple species stands on the development of estimation models, one hundred twenty-two randomly located points were selected from within hardwood stands (Table 2). All points were at least 30 m away from stand edges. Ninety-two randomly drawn points were used as training points, and the remaining thirty points were retained as test points. Of the ninety-two training points, fifty, and thirty randomly drawn points were selected as sets of training points for the development of AGB and forest parameter estimation models. Thus, two regression models were developed based on two different sets of training points. Thirty test points were used as independent test points for model assessment.

AGB and forest parameter estimation models for the interior pine stands

One hundred and eleven randomly located points were selected from within pine stands (Table 2). All points were at least 30 m away from stand edges. Eighty-one randomly drawn points were used as training points, and the remaining thirty points were retained for test points. Of the eighty-one training points, fifty, and thirty randomly drawn points were assigned as sets of training points for the development of AGB and forest parameter estimation models. Thus, two regression models were developed based on two different sets of training points for AGB and forest parameter estimation models of pine stands. Thirty test points were used as independent test points for model assessment.

4.3 Field measurement – Estimation of actual AGB in training and test points

Between January and August in 2006, field-based estimates of AGB were done for three hundred eighty randomly located points in the Whitehall Forest (Figure 2). Trees around each point were sampled using a BAF 10 prism. Per-0.09 ha (30×30 m) estimates of tree structure were developed for each point. The collected forest parameters were diameter at breast height (DBH) and total tree height. The location of each point was determined using a GPS unit (GeoExploer3; Trimble Navigation Limited) without onsite differential correction.

First, to estimate AGB of each field point, standing tree volume (ft^3), including saplings and nonmerchantable size trees, was derived using tree structure data with published allometric equations developed by Clark *et al*. (1986), and Clark and Saucier (1990). Those equations are listed in Table 3. Due to a lack of published allometric equations, some species were arbitrarily defined as other similar species. For example, volumes of *Quercus palustris* (pin oak) were calculated from a volume equation of northern red oak. To estimate AGB of each point, the conversion formula of a live tree carbon mass density (tons-c per ha) developed by Smith *et al.* (2004) was applied (Equation 1). Accordingly, the scale of AGB was converted into ton-c per 0.09 ha. Finally, total basal area (cm^2 per 0.09 ha) and mean tree height (m per 0.09 ha) were derived.

Table 3. Volumes (wood only) of major species found in the study area.

Species	DBH (inch)	Volume ($feet^3$)
yellow popular	< 11.0	$V = 0.00319\ (DBH^2\ Th)^{0.96001}$
	≥ 11.0	$V = 0.00221\ (DBH^2)^{1.03636}\ (Th)^{0.96001}$
sweetgum	< 11.0	$V = 0.00336\ (DBH^2\ Th)^{0.95017}$
	≥ 11.0	$V = 0.00120\ (DBH^2)^{1.16449}\ (Th)^{0.95017}$
blackgum	< 11.0	$V = 0.00476\ (DBH^2\ Th)^{0.91940}$
	≥ 11.0	$V = 0.00173\ (DBH^2)^{1.13000}\ (Th)^{0.91940}$
white oak	< 11.0	$V = 0.00343\ (DBH^2\ Th)^{0.95978}$
	≥ 11.0	$V = 0.00122\ (DBH^2)^{1.17575}\ (Th)^{0.95978}$
red oak	< 11.0	$V = 0.00228\ (DBH^2\ Th)^{1.00713}$
	≥ 11.0	$V = 0.00138\ (DBH^2)^{1.11144}\ (Th)^{1.00713}$
water oak	< 11.0	$V = 0.00459\ (DBH^2\ Th)^{0.93189}$
	≥ 11.0	$V = 0.00203\ (DBH^2)^{1.10193}\ (Th)^{0.93189}$
hickory	< 11.0	$V = 0.00319\ (DBH^2\ Th)^{0.96001}$
	≥ 11.0	$V = 0.00221\ (DBH^2)^{1.03636}\ (Th)^{0.96001}$
shortleaf pine	< 5.0	$V = 0.00211\ (DBH^2\ Th)^{1.01241}$
	≥ 5.0	$V = 0.00199\ (DBH^2)^{1.03101}\ (Th)^{1.01241}$
loblolly pine	≥ 3.0	$V = 0.00172\ (DBH^2\ Th)^{1.02990}$

* Th (total tree height), DBH (1.37 m above forest floor)

$$\textbf{Live tree carbon mass density} = \frac{353\left[0.0347 + \left\{1 - \exp\left(\frac{-(volume)}{312}\right)\right\}\right]}{2} \qquad \text{(Equation 1)}$$

* the unit of live tree carbon mass density is (ton-c / ha)
** *volume* = standing volume (m^3 / ha)

4.4 Satellite image data

<u>Image preprocessing</u>

Two Landsat TM 5 images, covering the study area (Path 18 Row 36 and Path 18 Row 37), were acquired on June 7, 2005 (Figure 3). The images were georeferenced to UTM NAD 86 Zone 17. Using 15 ground control points and a nearest-neighbor method, a root square mean error of 0.6 pixels was achieved, which implies ±18 m ground accuracy. The pixel size was set 30 m for all subscenes except TM band 6 (thermal band). Due to a coarse pixel resolution of 120 m, TM band 6 was not considered in this study. Haze and noise reduction procedures were applied to the image to eliminate unwanted spectral reflectance values in the TM images.

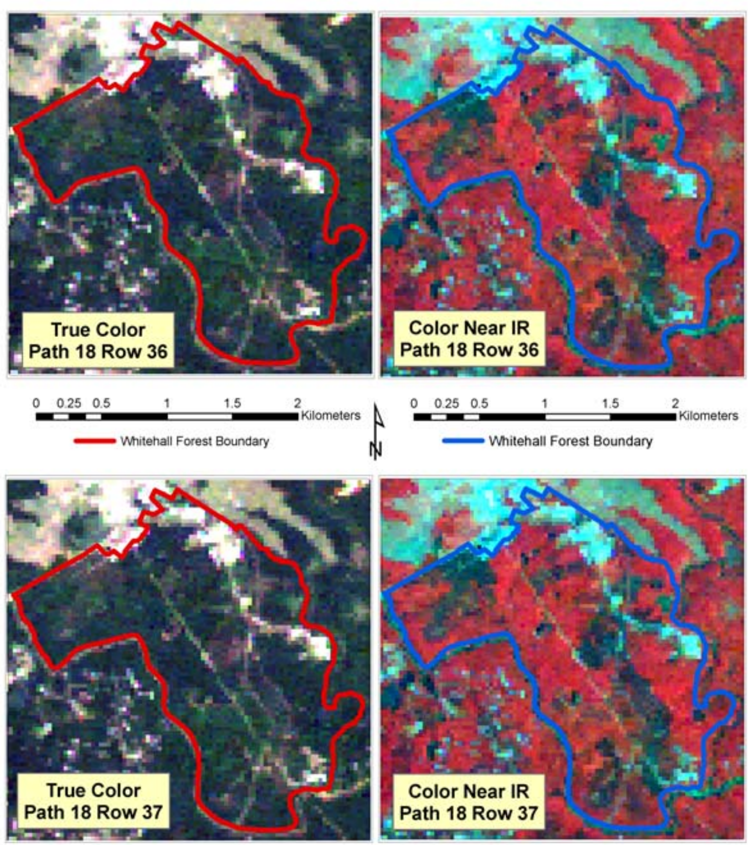


Figure 3. Two Landsat TM 5 images present the Whitehall Forest. As examples, true color (band combination of 1,2 and 3) and color infrared (band combination of 1,2 and 4) images are displayed.

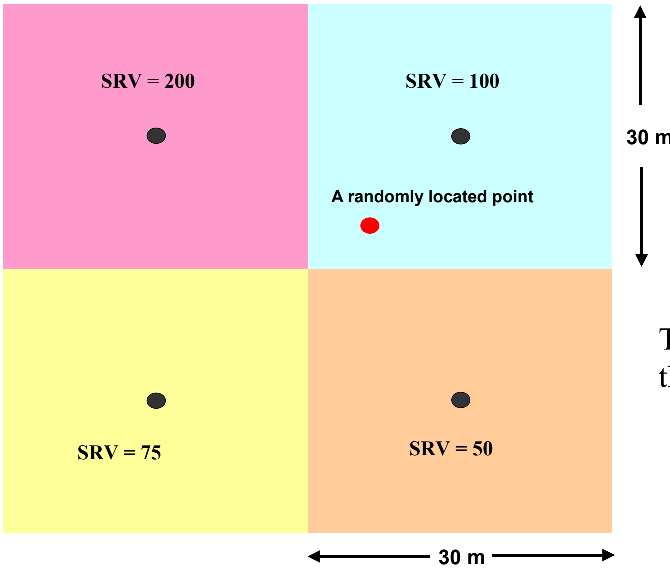
Image classification – Spectral reflectance value extraction

Five subscenes (TM bands 1-5 and 7 images) in a TM image (Path 18 Row 36) and three vegetation indices, NDVI, MVI5 and MVI7 (Freitas *et al.* 2005) were used for AGB estimation. This study applied two different approaches for spectral reflectance value extraction. First, a strict pixel-based (SPB) approach, which extracts reflectance values directly from a pixel containing a corresponding training point (Figure 4). Second, an inversely weighted Euclidean distance (IWED) approach, which averages spectral reflectance values of four closest pixels from each training point based on distances between each point to the center of these four closest pixels (Equation 2) (Figure 5).

$$\text{Spectral reflectance value} = \frac{\left\{\sum_{i=1}^{4}\left(\frac{x_i}{y_i}\right)\right\}}{\left\{\sum_{i=1}^{4}\left(\frac{1}{y_i}\right)\right\}} \qquad \text{(Equation 2)}$$

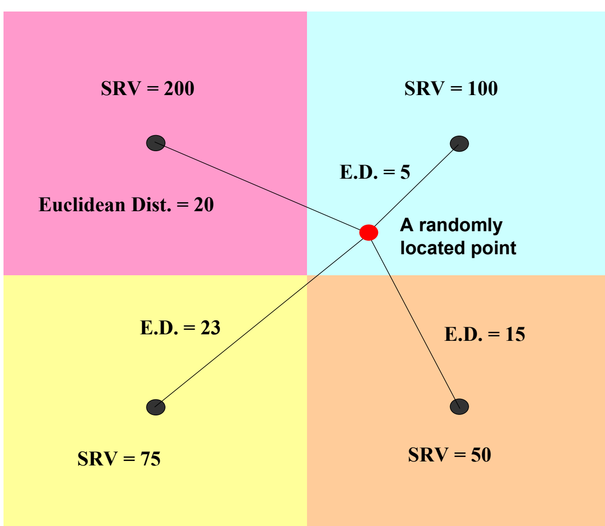
where: y_i = an Euclidean distance between a random point and a center of closest four pixels

x_i = a spectral reflectance value in a pixel



The spectral reflectance value (SRV) of this point is determined as 100.

Figure 4. A hypothetical example of the strict pixel-based (SPB) approach



$$SRV = \frac{\left(\frac{100}{5}+\frac{50}{15}+\frac{200}{20}+\frac{75}{23}\right)}{\left(\frac{1}{5}+\frac{1}{15}+\frac{1}{20}+\frac{1}{23}\right)} = \left(\frac{36.5942}{0.3601}\right) = 101.61$$

Thus, the spectral reflectance value (SRV) of this point is determined as 101.61.

Figure 5. A hypothetical example of the inversely weighted Euclidean distance (IWED) approach

Development of vegetation indices

Three vegetation indices, which were NDVI, MVI5 and MVI7 (Freitas *et al.* 2005), were developed using ERDAS Imagine software. The formulas of each vegetation index were listed in Equations 3-5.

$$\text{NDVI} = \frac{Band4 - Band3}{Band4 + Band3} \qquad \text{(Equation 3)}$$

$$\text{MVI5} = \frac{Band5 - Band3}{Band5 + Band3} \qquad \text{(Equation 4)}$$

$$\text{MVI7} = \frac{Band7 - Band3}{Band7 + Band3} \qquad \text{(Equation 5)}$$

Development of simple and stepwise regression models

The spectral reflectance values estimated from the training points, and the field measured AGB and forest parameters (basal area and tree height) were used to develop the regression models. First, simple regression models were developed using TM bands 1-5 and 7, and three vegetation indices (*e.g.* for the entire study site, there were four different sets of training points (n = 200,100, 50 and 30) with total nine independent variables; thus, 36 simple regression models were developed). The spectral reflectance values in TM bands and values in vegetation indices were the independent variables, and AGB and forest parameters from the training points were the dependent variables. Each simple regression model was evaluated using the coefficient of determination (R^2). Once a regression model with good predictive ability (higher R^2 models) was developed, AGB or forest parameters for the entire area should be predicted. Also, factors contributing to the development of strong R^2 models were investigated regarding different numbers of training points, and characteristics of TM bands and vegetation indices.

Second, multiple combinations of extracted reflectance values from TM bands and vegetation indices were used to develop stepwise regression models. The best combination of independent variables for AGB and forest parameter estimation was determined based on Akaike's Information Criterion (AIC). AIC is widely used as a criterion of model selection. While it may not select the best model, it selects a model, which works. Again, factors contributing to strong R^2 models were investigated regarding different numbers of training datasets, and characteristics of TM band and vegetation index combinations.

4.5 Accuracy assessment

Accuracy of AGB estimation models and other forest parameter models was assessed using randomly located test points that were not included in the development of the regression models. Each best predictive model (*e.g.* estimation of hardwood stands, estimation of pine stands) was selected to undergo an accuracy assessment. The accuracy of the predicted AGB was assessed using 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 field measured AGB from the independent test points.

Additionally, to examine the impact of numbers of test points on levels of R^2 in the accuracy assessment, a bootstrapping technique was used. The levels of R^2 based on 30 sets of thirty and fifty randomly drawn test points from eighty potential test points were compared using the predictions from the best AGB estimation model.

Finally, using an error matrix, accuracy levels in each best AGB estimation model from the entire study site, the interior forest stands, the hardwood stands, and the pine stands were computed and the results compared. Because the error matrix is generally used to evaluate output data in categorical formats (*e.g.* land type classification), the continuous AGB values were arbitrary organized into eight classes, each with an interval of 25 ton-c per 0.09 ha.

CHAPTER 5

Results

5.1. Overall summary

Coefficient of determination (R^2) of developed AGB, basal area, and height estimation models based on simple regression between field measured AGB, basal area, and height, and reflectance values in a single TM band or a vegetation index were low ($R^2 < 0.18$). Unlike some previous studies (*e.g.* Franklin 1986, Tortter *et al.* 1997), transformation (*e.g.* logarithmic and square root) of those independent variables did not improve R^2 values (See Appendix A). As a next step, estimation models were developed to perform stepwise regression with Akaike's Information Criterion (AIC) used to rank the models and determine the best model. However, results of best combination of independent variables in estimating AGB, basal area and tree height based on AIC did not show consistent trends (Appendix B-1 to B-22). For example, some models seemed to be the best when using only band 1, which one would assume to be the least suitable band because theoretically, the wavelengths of light captured in TM band 1 (blue spectral region) are the most easily scattered spectrum in the atmosphere. Thus, a majority of spectral information in band 1 was likely reflected from particles in the atmosphere. On the other hand, some models were developed using all bands and all these vegetation indices. However, all three vegetation indices were developed based on band 3, and either band 4, 5 or 7 (Equations 3-5); thus, for example, spectral information in bands 3 and 4, and NDVI are not independent. In other words, spectral information in bands 3 and 4, and NDVI would strongly be correlated in some degree. However, to maximize levels of R^2, all regression models were developed using all of the independent variables (bands 1-5 and 7, NDVI, MVI5 and MVI7) for AGB, basal area, and height estimation, and the spectral information from the bands and vegetation indices was assumed to be independent.

5.2 Development and assessment of regression models for the entire study site

Among three hundred randomly located training points, thirty, fifty, one hundred, and two hundred randomly drawn points were used to develop estimation models, which predicted total AGB (ton-c per 0.09 ha), total basal area (cm^2 per 0.09 ha), and mean total tree height (m per 0.09 ha). The regression models were developed using all nine independent variables, and field measured AGB, basal area, and tree height from training points. A maximum, minimum, average and standard deviation of coefficient of determination (R^2) of each model were derived based on 30 sets of randomly drawn training points (Table 4) (Appendix A-1 to -8). Lower numbers of training points produced better regression models, although the worst model produced was about the same level of R^2 in each case.

Lower numbers of training points, however, resulted in larger variation in R^2 among 30 sets of randomly drawn training points. For example, while the standard deviation of R^2 for AGB estimation model based on thirty training points was 0.1185, the standard deviation of R^2 based on two hundred training points was 0.0307 based on the SPB approach. Additionally, although the SPB approach and the IWED approach were not much different when it came to R^2 values, the IWED approach seemed to result in the development of higher R^2 maximum, minimum and average models for AGB and basal area, but not height. Although those differences would be negligible overall, some models (*e.g.* for AGB estimation model based on 30 training points) derived using the SPB approach had R^2 values that were 0.100 higher.

Table 4. Coefficient of determination (R^2) between nine independent variables and field measured AGB, basal area, and height based on (a) thirty, (b) fifty, (c) one hundred, and (d) two hundred training points. Maximum, minimum, average and standard deviation (SD) were determined based on 30 different randomly drawn sets of those numbers of training points.

(a) Based on thirty training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.7774	0.6749	0.6159	0.6183	0.6830	0.7070
Min	0.2288	0.1320	0.2095	0.1364	0.1525	0.1955
Average	0.4395	0.4632	0.4255	0.4289	0.4237	0.4167
SD	0.1185	0.1179	0.1033	0.1219	0.1200	0.1224

(b) Based on fifty training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.5206	0.5501	0.4739	0.5516	0.6434	0.5867
Min	0.0947	0.1333	0.0466	0.1301	0.1874	0.1039
Average	0.3080	0.3347	0.2653	0.3047	0.4302	0.3259
SD	0.1007	0.0862	0.1040	0.0799	0.1174	0.1183

(c) Based on one hundred training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.4187	0.3237	0.3551	0.2790	0.3533	0.3353
Min	0.1480	0.1252	0.1119	0.0754	0.1465	0.0996
Average	0.2596	0.2073	0.2208	0.1706	0.2409	0.2120
SD	0.0636	0.0533	0.0598	0.0518	0.0458	0.0659

(d) Based on two hundred training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.2514	0.2690	0.2012	0.2408	0.2393	0.2318
Min	0.1231	0.1329	0.0832	0.0954	0.0971	0.0958
Average	0.1795	0.1885	0.1313	0.1506	0.1396	0.1624
SD	0.0307	0.0346	0.0296	0.0364	0.0304	0.0357

[a] Spectral reflectance value extraction based on strict pixel-based (SPB) approach
[b] Spectral reflectance value extraction based on inversely weighted Euclidean distance (IWED) approach

The best regression models using different numbers of training points (30, 50, 100 and 200) were selected to undergo an accuracy assessment (Table 5), and coefficients and an intercept of each best predictive model of AGB, basal area, and height are summarized in Table 12. Interestingly, regression models with higher R^2 values did not result in higher accuracy levels. For example, although an AGB estimation model with R^2 of 0.7774 was derived based on thirty training points with the SPB approach, this model resulted in R^2 of 0.0370 in the accuracy assessment. On the other hand, while the AGB estimation model with an R^2 of 0.1231 that was based on two hundred training points using the SPB approach, this model resulted in R^2 of 0.2015 in the accuracy assessment. Additionally, accuracy levels between the SPB and IWED approach did not differ very much.

Table 5. The accuracy assessment of developed regression estimation models for the study site.

Dependent variables	Number of training points	Approach [a]	Model $R^{2\ b}$	Number of test points	Model assessment in $R^{2\ c}$
AGB	30	SPB	0.7774	50	0.0370
Basal Area	30	SPB	0.6159	50	0.0091
Height	30	SPB	0.6830	50	0.0291
AGB	30	IWED	0.6749	50	0.0913
Basal Area	30	IWED	0.6183	50	0.0791
Height	30	IWED	0.7070	50	0.1258
AGB	50	SPB	0.5206	50	0.1961
Basal Area	50	SPB	0.4739	50	0.1075
Height	50	SPB	0.6434	50	0.0497
AGB	50	IWED	0.5501	50	0.1695
Basal Area	50	IWED	0.5516	50	0.1374
Height	50	IWED	0.5867	50	0.0555
AGB	100	SPB	0..4187	50	0.1816
Basal Area	100	SPB	0.3551	50	0.0839
Height	100	SPB	0.3533	50	0.1681
AGB	100	IWED	0.3237	50	0.1353
Basal Area	100	IWED	0.2790	50	0.2133
Height	100	IWED	0.0996	50	0.0851
AGB	200	SPB	0.1231	50	0.2015
Basal Area	200	SPB	0.2012	50	0.0574
Height	200	SPB	0.2393	50	0.1695
AGB	200	IWED	0.2690	50	0.2806
Basal Area	200	IWED	0.2408	50	0.2173
Height	200	IWED	0.2318	50	0.1007

[a] Approach for spectral reflectance value extraction, strict pixel-based (SPB) and inversely weighted Euclidean distance (IWED).
[b] R^2 of regression model between spectral reflectance value and field measured AGB, basal area, or height from training points.
[c] R^2 between field measured AGB from test points and estimated AGB from regression model.

5.3 Development and assessment of regression models for the interior forest stands

Among three hundred randomly located training points, thirty, fifty and one hundred randomly drawn points were used to develop estimation models, which predicted total AGB (ton-c per 0.09 ha), total basal area (cm^2 per 0.09 ha), and mean total tree height (m per 0.09 ha). However, only training points located at least 30 m away from stand edges were selected.

Regression models were developed using all nine independent variables, and field measured AGB, basal area, and tree height from training points. A maximum, minimum, average and standard deviation of coefficient of determination (R^2) of each model were derived based on 30 sets of randomly drawn training points (Tables 6) (Appendix A-9 to -14).

Here again, lower numbers of training points resulted in larger variation among 30 sets of randomly drawn training points regarding R^2. For example, while the standard deviation of R^2 for AGB estimation model based on thirty training points was 0.1303, the standard deviation of R^2 based on one hundred training points was 0.0456, both based on the SPB approach. And again, lower numbers of training points tended to have larger maximum, minimum and average R^2. This tendency seemed to be consistent for basal area and height estimation models. Additionally, although the SPB and the IWED approaches did not result in much difference regarding R^2, to some degree the IWED approach seemed to result in the development of higher R^2 maximum, minimum and average models for AGB, basal area, and height. However, the differences were small overall. Additionally, while training points located at least 30 m away from stand edges were selected, these results are not much different than when points near edges were used (Tables 4).

Table 6. Coefficient of determination (R^2) between nine independent variables and field measured AGB, basal area, and height based on (a) thirty, (b) fifty, and (c) one hundred training points in the interior forest stands. Maximum, minimum, average and standard deviation (SD) were determined based on 30 different sets of those numbers of training points

(a) Based on thirty training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.7175	0.7432	0.6807	0.6540	0.6842	0.7218
Min	0.1988	0.2840	0.1563	0.2107	0.1939	0.1590
Average	0.4363	0.4502	0.4007	0.4155	0.4618	0.4451
SD	0.1303	0.1005	0.1297	0.1110	0.1328	0.1688

(b) Based on fifty training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.6795	0.5602	0.5703	0.4756	0.5312	0.5803
Min	0.1614	0.1857	0.1458	0.1073	0.1632	0.1711
Average	0.3741	0.3908	0.3285	0.3412	0.3383	0.3508
SD	0.1075	0.0940	0.1098	0.0975	0.0987	0.0925

(c) Based on one hundred training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.4107	0.4062	0.3304	0.3700	0.2948	0.3833
Min	0.2127	0.1878	0.1758	0.1540	0.1268	0.1076
Average	0.3044	0.3147	0.2347	0.2526	0.2242	0.2436
SD	0.0456	0.0550	0.0413	0.0525	0.0489	0.0685

[a] Spectral reflectance value extraction based on strict pixel-based (SPB) approach
[b] Spectral reflectance value extraction based on inversely weighted Euclidean distance (IWED) approach

The best regression models from different numbers of training points (30, 50 and 100) were selected to undergo an accuracy assessment (Table 7), and coefficients and an intercept of each best predictive model of AGB, basal area, and height are summarized in Table 12. Here again, models with higher R^2 values did not result in higher accuracy levels. For example, although an AGB estimation model with R^2 of 0.7175 was derived based on thirty training points with the SPB approach, this model resulted in R^2 of 0.1400 in the accuracy assessment. On the other hand, an AGB estimation model with an R^2 of 0.4107 that was derived based on one hundred training points using the SPB approach, resulted in an R^2 of 0.1259 in the accuracy assessment. However, one AGB estimation model with R^2 of 0.5602 that was derived based on fifty training points using the IWED approach in an R^2 of 0.2438 in the accuracy assessment.

Table 7. The accuracy assessment of developed regression estimation models for the interior forest stands. Any points located with in 30 m from stand edges were removed.
5.4 Development and assessment of regression models for the hardwood stands

Dependent variables	Number of training points	Approach [a]	Model $R^{2\ b}$	Number of test points	Model assessment in $R^{2\ c}$
AGB	30	SPB	0.7175	50	0.1400
Basal Area	30	SPB	0.6807	50	0.0559
Height	30	SPB	0.6842	50	0.0074
AGB	30	IWED	0.7432	50	0.0979
Basal Area	30	IWED	0.6540	50	0.0432
Height	30	IWED	0.7218	50	0.0316
AGB	50	SPB	0.6795	50	0.1664
Basal Area	50	SPB	0.5703	50	0.1006
Height	50	SPB	0.5312	50	0.1097
AGB	50	IWED	0.5602	50	0.2438
Basal Area	50	IWED	0.4756	50	0.1675
Height	50	IWED	0.5803	50	0.0923
AGB	100	SPB	0.4107	50	0.1259
Basal Area	100	SPB	0.3304	50	0.0939
Height	100	SPB	0.2948	50	0.0065
AGB	100	IWED	0.4062	50	0.1701
Basal Area	100	IWED	0.3700	50	0.0830
Height	100	IWED	0.3833	50	0.1089

[a] Approach for spectral reflectance value extraction, strict pixel-based (SPB) and inversely weighted Euclidean distance (IWED).
[b] R^2 of regression model between spectral reflectance value and field measured AGB, basal area, or height from training points.
[c] R^2 between field measured AGB from test points and estimated AGB from regression model.

5.4 Development and assessment of regression models for the hardwood stands

Among the hundred twenty-two randomly located training points in hardwood stands, thirty and fifty randomly drawn points were used to develop estimation models, which predicted total AGB (tons-c per 0.09 ha), total basal area (cm^2 per 0.09 ha), and mean total tree height (m per 0.09 ha) in the hardwood stands. Also, all points were at least 30 m away from stand edges. Regression models were developed using all nine independent variables, and field measured AGB, basal area, and tree height from training points. A maximum, minimum, average and standard deviation of coefficient of determination (R^2) of each model were again derived based on 30 sets of randomly drawn training points (Tables 8) (Appendix A-15 to -18).

As noted before, lower numbers of training points resulted in larger variation among 30 sets of randomly drawn training points. For example, while the standard deviation of R^2 for AGB estimation model based on thirty training points was 0.1194, the standard deviation of R^2 based on fifty training points was 0.0676, both based on the SPB approach. Also, lower numbers of training points tended to have larger maximum, minimum and average R^2. This tendency seemed to be consistent for basal area and height estimation models. Additionally, although the SPB and the IWED approaches did not result in very different models in general, some models such as height based on thirty training points were quite different. Finally, the overall results regarding hardwood models showed R^2 values lower than these estimation models from the entire study site and the interior forest stands by about 0.07-0.10 (Tables 4 and 6).

Table 8. Coefficient of determination (R^2) between nine independent variables and field measured AGB, basal area, and height based on (a) thirty, and (b) fifty training points in the hardwood stands. Maximum, minimum, average and standard deviation (SD) were determined based on 30 different sets of those numbers of training points.

(a) Based on thirty training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.6860	0.6490	0.7027	0.6252	0.5206	0.6802
Min	0.1278	0.1268	0.1162	0.1943	0.1242	0.1269
Average	0.2907	0.3664	0.2852	0.3728	0.3268	0.4367
SD	0.1194	0.1206	0.1262	0.1013	0.1170	0.1445

(b) Based on fifty training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.3746	0.4067	0.3948	0.4535	0.4206	0.4884
Min	0.1116	0.1542	0.1052	0.1728	0.1387	0.1925
Average	0.2350	0.2733	0.2254	0.2792	0.2697	0.3280
SD	0.0676	0.0701	0.0735	0.0768	0.0738	0.0767

[a] Spectral reflectance value extraction based on strict pixel-based (SPB) approach
[b] Spectral reflectance value extraction based on inversely weighted Euclidean distance (IWED) approach

One again, the best regression models from different numbers of training points (30 and 50) were selected to undergo an accuracy assessment (Table 9), and coefficients and an intercept of each best predictive model of AGB, basal area, and height were summarized in Table 12. And once again, models with higher R^2 values did not result in higher accuracy levels. For example, the AGB estimation model with an R^2 of 0.6860 was derived based on thirty training points with the SPB approach, this model resulted in R^2 of 0.0137 in the accuracy assessment.

Table 9. The accuracy assessment of developed regression estimation models for the interior hardwood stands. Any points located with in 30 m from stand edges were removed.

Dependent variables	Number of training points	Approach [(a)]	R^2 of the model [(b)]	Number of test points	Model assessment in $R^{2\,(c)}$
AGB	30	SPB	0.6860	30	0.0137
Basal Area	30	SPB	0.7027	30	0.0084
Height	30	SPB	0.5206	30	0.0453
AGB	30	IWED	0.6490	30	0.0062
Basal Area	30	IWED	0.6252	30	0.0017
Height	30	IWED	0.6802	30	0.0629
AGB	50	SPB	0.3746	30	0.0806
Basal Area	50	SPB	0.3948	30	0.0285
Height	50	SPB	0.4206	30	0.0373
AGB	50	IWED	0.4067	30	0.0362
Basal Area	50	IWED	0.4535	30	0.0085
Height	50	IWED	0.4884	30	0.0427

[a] Approach for spectral reflectance value extraction, strict pixel-based (SPB) and inversely weighted Euclidean distance (IWED).
[b] R^2 of regression model between spectral reflectance value and field measured AGB, basal area, or height from training points.
[c] R^2 between field measured AGB from test points and estimated AGB from regression model.

5.5 Development and assessment of regression models for the pine stands

From the one hundred-eleven randomly located training points in pine stands, thirty and fifty randomly drawn points were used to develop estimation models, which predicted total AGB (tons-c per 0.09 ha), total basal area (cm^2 per 0.09 ha), and mean total tree height (m per 0.09 ha) in the pine stands. Also, all points were at least 30 m away from stand edges. Regression models were developed using all nine independent variables, and field measured AGB, basal area, and tree height from training points. A maximum, minimum, average and standard deviation of coefficient of determination (R^2) of each model were derived based on 30 sets of randomly drawn training points (Tables 10) (Appendix A-19 and -22).

As noted in earlier tests, lower numbers of training points resulted in larger variation among 30 sets of randomly drawn training points. For example, while the standard deviation of R^2 for AGB estimation model based on thirty training points was 0.1003, the standard deviation of R^2 based on fifty training points was 0.0657, both based on the SPB approach. Also, lower numbers of training points tended to have larger maximum, minimum, and average R^2. This tendency seemed to be consistent for basal area and height estimation models. Additionally, the differences between the SPB and the IWED approaches were minimal. At last, the results based on thirty training points seemed to be the lowest here, compared to regression models of the entire study site, the interior forest stands, the hardwood stands by about 0.12-0.20 in R^2.

Table 10. Coefficient of determination (R^2) between nine independent variables and field measured AGB, basal area, and height based on (a) thirty, and (b) fifty training points in the pine stands. Maximum, minimum, average and standard deviation (SD) were determined based on 30 different sets of those numbers of training points.

(a) Based on thirty training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.5691	0.5955	0.5844	0.6181	0.5337	0.6063
Min	0.1732	0.1832	0.2145	0.2119	0.2592	0.2333
Average	0.3718	0.3845	0.4108	0.4384	0.5306	0.5018
SD	0.1003	0.1053	0.0994	0.1053	0.1070	0.1176

(b) Based on fifty training points

	Above ground biomass		Basal area		Height	
	SPB [a]	IWED [b]	SPB [a]	IWED [b]	SPB [a]	IWED [b]
Max	0.4467	0.3756	0.4701	0.4521	0.5337	0.6063
Min	0.1696	0.1772	0.1725	0.2011	0.3372	0.2546
Average	0.3090	0.3015	0.3397	0.3485	0.4404	0.4467
SD	0.0657	0.0482	0.0670	0.0577	0.0558	0.0803

[a] Spectral reflectance value extraction based on strict pixel-based (SPB) approach
[b] Spectral reflectance value extraction based on inversely weighted Euclidean distance (IWED) approach

The best regression models were once again selected to undergo an accuracy assessment (Table 11), and coefficients and an intercept of each best predictive model of AGB, basal area, and height were summarized in Table 12. The results were slightly different from other previous results. Here, R^2 values seemed to be independent from levels of R^2 derived from the regression models. The AGB estimation model with an R^2 of 0.4467 was derived based on fifty training points with the SPB approach, this model resulted in R^2 of 0.2058 in the accuracy assessment. This result was different from the case of the entire study site, the interior forest stands, and the hardwood stands.

Table 11. The accuracy assessment of developed regression estimation models for the interior pine stands. Any points located with in 30 m from stand edges were removed.

Dependent variables	Number of training points	Approach [a]	Model $R^{2\,b}$	Number of test points	Model assessment in $R^{2\,c}$
AGB	30	SPB	0.5691	30	0.0162
Basal Area	30	SPB	0.5844	30	0.0057
Height	30	SPB	0.5337	30	0.0004
AGB	30	IWED	0.5955	30	0.0006
Basal Area	30	IWED	0.6181	30	0.0010
Height	30	IWED	0.6063	30	0.0001
AGB	50	SPB	0.4467	30	0.2058
Basal Area	50	SPB	0.4701	30	0.0403
Height	50	SPB	0.5337	30	0.0133
AGB	50	IWED	0.3756	30	0.0153
Basal Area	50	IWED	0.4521	30	0.0020
Height	50	IWED	0.6063	30	0.0001

[a] Approach for spectral reflectance value extraction, strict pixel-based (SPB) and inversely weighted Euclidean distance (IWED).
[b] R^2 of regression model between spectral reflectance value and field measured AGB, basal area, or height from training points.
[c] R^2 between field measured AGB from test points and estimated AGB from regression model.

Table 12. Coefficients and an intercept of each best predictive model for AGB, basal area, and height estimations for (a) the entire study site, (b) the interior forest stands, (c) the hardwood stands, and (d) the pine stands

(a) The entire study site

Dependent variable	Coefficient									Intercept
	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7	NDVI	MVI5	MVI7	
AGB	41.99	-23.93	35.89	-0.77	14.43	-97.45	9.51	6.77	-27.28	348.41
Basal area	341.77	-457.60	422.62	372.77	-999.01	1098.68	72.71	-617.68	513.68	-42,460.13
Height	2.61	0.04	15.03	0.52	-0.32	-18.77	3.97	0.18	-6.71	240.59

(b) The interior forest stands

Dependent variable	Coefficient									Intercept
	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7	NDVI	MVI5	MVI7	
AGB	-19.66	31.04	-139.18	-0.98	23.10	61.42	-29.12	13.46	18.97	1,944.73
Basal area	-859.63	-598.54	-2,781.85	-232.32	906.98	2,524.33	-887.33	482.01	832.64	22,293.15
Height	-1.71	-1.44	4.81	-0.18	1.91	-7.14	1.00	0.59	-2.50	281.73

(c) The hardwood stands

Dependent variable	Coefficient									Intercept
	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7	NDVI	MVI5	MVI7	
AGB	45.65	-9.94	128.34	-53.29	38.06	4.61	41.59	20.81	7.97	-16,876.38
Basal area	1,849.52	-428.86	5,296.67	-1,838.75	793.61	958.04	1,683.07	446.99	596.82	-680,395.04
Height	6.12	-4.47	20.52	-6.79	7.14	-10.88	5.66	4.31	-2.78	-1,649.71

(d) The pine stands

Dependent variable	Coefficient									Intercept
	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7	NDVI	MVI5	MVI7	
AGB	-3.58	19.50	175.89	17.69	-56.20	-105.69	46.14	-31.90	-37.61	1,219.19
Basal area	-470.68	902.49	-383.13	738.80	-963.13	-161.91	-26.28	-654.48	18.19	102,912.39
Height	-2.17	3.15	-0.92	3.42	-6.95	9.80	0.22	-4.98	3.55	-29.17

5.6 Different sets of test points for the accuracy assessment

Because lower numbers of training points tended to result in regression models with higher R^2 values, here, two different sets of test points were used to undergo an accuracy assessment. This accuracy assessment was only taken for the entire study site for AGB estimation, and the best predictive model with R^2 of 0.7774 derived from thirty training points with the SPB approach was selected.

Among eighty test points, 30 different sets of thirty and fifty random test points were assigned for the test points. The results were presented in Table 13. Here, one set of thirty random test points resulted in the highest R^2 value of 0.1549 in the accuracy assessment, but two sets of thirty random test points resulted in an $R^2 \leq 0.0001$. On the other hand, one set of fifty random test points resulted in smaller standard deviation of 0.0214. However, the difference between thirty and fifty test points seemed to be small overall.

Table 13. The accuracy assessment for AGB estimation in the entire study site. The selected model with R^2 of 0.7774 was tested (a) 30 sets of thirty randomly drawn test points, and (b) 30 sets of fifty randomly drawn test points.

(a) R^2 in the accuracy assessment based on thirty test points

0.0994	0.0023	0.0767	0.0009	0.0059	0.0074		
0.1044	0.0610	0.0009	0.0661	< 0.0001	0.1549	**Maximum**	**0.1549**
0.0047	0.0063	0.0017	0.0196	0.0000	0.0237	**Minimum**	**< 0.0001**
< 0.0001	0.0763	0.0096	0.0054	0.0184	0.0071	**Average**	**0.0266**
0.0215	0.0012	0.0168	0.0010	0.0040	0.0011	**SD**	**0.0397**

(b) R^2 in the accuracy assessment based on fifty test points

0.0169	0.0138	0.0157	0.0227	0.0100	0.0130		
0.0207	0.058	0.0234	0.0024	0.0253	0.0129	**Maximum**	**0.0463**
0.0463	0.0003	0.0393	0.0053	0.0391	0.0005	**Minimum**	**0.0005**
0.0068	0.0635	0.0048	0.0059	0.0384	0.0097	**Average**	**0.0201**
0.0035	0.0188	0.0224	0.0019	0.0581	0.0045	**SD**	**0.0214**

5.7 Accuracy assessment using error matrix

The accuracy assessment noted using the coefficient of determination (R^2) was low overall (*e.g.* the entire study area and the interior forest stands). Here, as another way of accuracy assessment approach, error matrix was used to evaluate levels of accuracy in developed regression models (Table 14). In general, error matrix is used for evaluating categorical data, such as land type classification. Because of such limitation in error matrix, estimated AGB (ton-c per 0.09 ha) were arbitrary organized into eight AGB classes as shown in Table 14. For the entire study site, the best regression model with R^2 of 0.7774 based on thirty training point with the SPB approach was used to estimate AGB. For the interior forest stands, the best regression model with R^2 of 0.7175 based on thirty training point with the SPB approach was used to estimate AGB. For the hardwood stands, the best regression model with R^2 of 0.6860 based on thirty training point with the SPB approach was used to estimate AGB. At last, for the pine stands, the best regression model with R^2 of 0.5961 based on thirty training point with the SPB approach was used to estimate AGB.

Overall accuracy in all four results was low. Highest overall result had 47% in the pine stands while KHAT was only 0.1279 (Table 14-d). Also, results of the interior forest stands (Table 14-b) and hardwood stands (Table 14-c) had a similar level in KHAT, but the entire study site had a KHAT of 0.0651 (Table 14-a).

Table 14. The accuracy assessment using error matrices for (a) the entire study site, (b) the interior forest stands, (c) the hardwood stands, and (d) the pine stands. Each best regression model to predict AGB in (a)-(d) was selected.

(a) The entire study site

Estimated AGB (ton-c per 0.09 ha) from regression model	Field measured AGB (ton-c per 0.09 ha) from test points: < 0	0 - 25	26 - 50	51 - 75	76 - 100	101 - 125	126 - 150	151 - 175	175 <	Total Points	Users' Accuracy
< 0	0	1	1	1	0	0	0	0	0	3	0%
0 - 25	0	10	4	2	3	0	0	0	0	19	53%
26 - 50	0	13	4	4	0	0	2	0	0	23	16%
51 - 75	0	4	8	8	3	0	1	1	0	25	32%
76 - 100	0	0	2	2	1	0	1	0	0	6	17%
101 - 125	0	0	1	1	0	0	0	0	0	2	0%
126 - 150	0	1	0	1	0	0	0	0	0	2	0%
151 - 175	0	0	0	0	0	0	0	0	0	0	0%
175 <	0	0	0	0	0	0	0	0	0	0	0%
Total Points	0	29	20	19	7	0	4	1	0	**80**	
Producer's Accuracy	100%	34%	20%	42%	14%	100%	0%	0%	0%		

Overall accuracy: 29% KHAT: 0.0651

(b) The interior forest stands

Estimated AGB (ton-c per 0.09 ha) from regression model	Field measured AGB (ton-c per 0.09 ha) from test points: < 0	0 - 25	26 - 50	51 - 75	76 - 100	101 - 125	126 - 150	151 - 175	175 <	Total Points	Users' Accuracy
< 0	0	0	0	0	0	1	0	0	0	1	0%
0 - 25	0	7	7	1	1	0	0	0	0	16	44%
26 - 50	0	5	4	3	0	0	0	0	1	13	27%
51 - 75	0	3	3	4	1	0	2	2	0	15	27%
76 - 100	0	0	0	2	2	0	0	0	0	4	50%
101 - 125	0	0	0	1	0	0	0	0	0	1	0%
126 - 150	0	0	0	0	0	0	0	0	0	0	100%
151 - 175	0	0	0	0	0	0	0	0	0	0	0%
175 <	0	0	0	0	0	0	0	0	0	0	0%
Total Points	0	15	14	11	4	1	2	2	1	**50**	
Producer's Accuracy	100%	47%	29%	36%	50%	100%	0%	0%	0%		

Overall accuracy: 34% KHAT: 0.1298

(c) The hardwood stands

Estimated AGB (ton-c per 0.09 ha) from regression model	Field measured AGB (ton-c per 0.09 ha) from test points: < 0	0 - 25	26 - 50	51 - 75	76 - 100	101 - 125	126 - 150	151 - 175	Total Points	Users' Accuracy
< 0	0	0	0	0	0	0	0	0	0	100%
0 - 25	0	3	0	0	0	0	0	0	3	100%
26 - 50	0	2	2	2	1	0	0	0	7	20%
51 - 75	0	3	3	4	0	0	0	0	10	40%
76 - 100	0	0	1	3	3	0	0	1	8	38%
101 - 125	0	0	0	0	2	0	0	0	2	100%
126 - 150	0	0	0	0	0	0	0	0	0	100%
151 - 175	0	0	0	0	0	0	0	0	0	100%
Total Points	0	8	6	9	6	0	0	1	**30**	
Producer's Accuracy	100%	38%	33%	44%	50%	100%	0%	0%		

Overall accuracy: 40%   KHAT: 0.1208

(d) The pine stands

Estimated AGB (ton-c per 0.09 ha) from regression model	Field measured AGB (ton-c per 0.09 ha) from test points: < 0	0 - 25	26 - 50	51 - 75	76 - 100	101 - 125	126 - 150	151 - 175	Total Points	Users' Accuracy
< 0	0	1	0	0	0	0	0	0	1	0%
0 - 25	0	9	2	3	0	0	0	0	14	64%
26 - 50	0	5	4	1	0	0	0	0	10	100%
51 - 75	0	2	1	1	0	0	0	0	4	25%
76 - 100	0	0	1	0	0	0	0	0	1	0%
101 - 125	0	0	0	0	0	0	0	0	0	100%
126 - 150	0	0	0	0	0	0	0	0	0	100%
151 - 175	0	0	0	0	0	0	0	0	0	100%
Total Points	0	17	8	5	0	0	0	0	**30**	
Producer's Accuracy	100%	53%	50%	20%	100%	100%	0%	0%		

Overall accuracy: 47%   KHAT: 0.1279

CHAPTER 6

Discussion

6.1 The relationship between numbers of training points and model R^2 values

The study had an objective of testing regression analysis, as a possible method for estimating above ground biomass (AGB) in ton-c per 0.09 ha using a single Landsat Thematic Mapper 5 (Landsat TM) imagery. The goal of this study was to be able to develop regression models that could provide users the ability to predict AGB, basal area and tree height with a reasonable degree of accuracy in the pine and hardwood forests typical of the Piedmont of Georgia. A bootstrapping technique was used to draw a small set of training points from a larger set of potential training points, in order to determine:

a) Whether a model with a high coefficient of determination (R^2) value could be developed
b) The repeatability of model quality, as expressed by the maximum, minimum, average, and standard deviation of R^2 model values

What I found was that there was so much variability in the large set of sample of training points that lower R^2 values occurred as sample training points used in regression analysis process increased. This was the case when estimates were made for all tree species over the entire study site, all tree species in the interior forest stands, hardwood stands, and pine stands. Thus, one conclusion from this study is that with a smaller number of training points, a better fit with the nine independent variables (six Landsat TM bands and three vegetation indices) could be obtained.

6.2 The relationship between model R^2 value and accuracy level

The best AGB estimation model for all tree species over the entire study site, using thirty training points with the strict pixel-based (SPB) approach, had an R^2 value of 0.7774, which by itself seems impressive. However, this one model is simply the best of 30 different regression models developed from 30 different sets of thirty training points. The average quality of the AGB estimation models for all tree species over the entire study site was not very good (R^2 = 0.4395), and the standard deviation was fairly wide (0.1185). When subjected to model validation processes, I found that there was not much agreement between the best model and an independent set of test (validation) points. In other words, accuracy levels of developed models were fairly low. I went further to select from the separate set of test points a subset of 30, and repeated this 30 times as well. The agreement of the field measured AGB from these bootstrapped test points with the predicted AGB from the best overall model was not promising (*e.g.* very low). Similarly, I selected from the separate set of test points a subset of 50, and repeated this 30 times. Again, the agreement of the field measured AGB from these bootstrapped test points with the predicted AGB from the best overall model was not promising. Thus, numbers of test points used in the accuracy assessment may not have an effect on the model validation. I then developed an error matrix using categories of AGB (predicted and field measured), and found low agreement as well. Therefore, for the overall AGB model, while a few regression models seem to have high R^2 values, each seems to fail validation tests. Thus, my confidence in estimating AGB from a single Landsat TM image in the pine and hardwood stands of the Piedmont of Georgia is low. However, generally models that fit the training data better (higher R^2 values) are often "overfitted" and have numerous variables that go into them, so that while trying to predict validation data, so one gets poor agreement.

6.3 Impact of normality of independent variables and effective vegetation indices

One reason for the low correspondence in actual *vs.* predicted AGB values may be the non-normality of the independent variables (Foody *et al.* 2001, Ingram *et al.* 2005). I tested each independent variable for normality, and most failed based on Kolmogrov-Smirnov test values. Transformations (logarithmic and square root) were applied to the data, with the hope that normality could be achieved; however, normality tests indicated that the transformed data were non-normal as well. In general, stepwise regression technique was used to try to bring only the statistically significant independent variables into each regression model. In this study, selections of independent variables into regression models were based on Akaike's Information Criterion (AIC), which allows non-significant variables to enter the model if the overall model fit to the data is better, but this process had little effect on overall quality of the regression models (See Appendix A). This was a more efficient way of approaching the problem of developing regression model, than simply trying all possible combinations of variables. However, from this approach, I found that the normality of independent variables did not seem to relate to levels of R^2 in developed models. For example, the regression model with R^2 of 0.7774 was developed using four independent variables that had a normal distribution and five independent variables that had a non-normal distribution. On the other hand, a regression model with $R^2 = 0.2288$ was developed using five independent variables with a normal distribution and four independent variables with a non-normal distribution (Appendix C). Therefore, future work in this area may want to concentrate on logical combinations of independent variables, since some of them (*e.g.* NDVI) are correlated with or without normality. In addition, while the independent variables were ones that were suggested from the literature, a second area of future work could involve the development of a new vegetation index that better discriminates the differences in hardwood and pine (in the infrared region), and better discriminates older and younger stands of trees (since this is an inherent problem for hardwood). Additionally, some articles reported positive results, which estimated volume or AGB in conifer-dominated forestlands, such as in the Pacific Northwest (Ripple *et al.* 1991). In general, those stand structures differs from typical southeast pine-dominated forestlands where canopy openings are larger. Consequently, forest floor conditions would largely affect spectral information in the Landsat TM imagery. For example, spectral information should differ greatly between recently applied prescribed burn stands and flourished understory vegetation (*e.g.* low shrubs) in pine stands. Thus, a third area of future work could involve the development of a new approach that minimizes the effect of spectral reflectance information from forest floors.

6.4 Impact of uncertainty of field points on the development of regression models

Since field point (training and test) locations were randomly located, and did not necessarily correspond to the centers of Landsat pixels, an inversely weighted Euclidean distance (IWED) approach to arriving at spectral reflectance values was used, with the hope that it too would increase agreement between field measured and predicted AGB. Since reflectance values from Landsat data may change considerably from one pixel to the next, I had hoped to capture this uncertainty with the IWED approach. However, there is also some uncertainty in the GPS data that represent each point location (error in ± 5-10 m); therefore, it is not unreasonable to assume that the results are very similar to the SPB approach, since the error may be randomly and uniformly distributed around each point location.

6.5 Impact of stand edges on development of regression models

Sensing that pixels near edges of stands, and perhaps containing more variability than interior pixels, may have contributed to the high disagreement between field measured and predicted AGB, I reduced the set of training points to contain only those significantly within the boundaries of forested areas. The hypothesis was that these training points would allow the development of a higher quality AGB regression model, however this partitioning of the training data did not yield better regression models.

6.6 Effect of mixed species stands on development of regression models

When developing regression models to predict AGB in only hardwood stands or only pine stands, I found similar results: a few of the regression models seemed to have high quality (as demonstrated by high R^2 values); the higher quality regression models were found with the lower number of training points; and validation tests failed in each case. One extension of this work may be to build a better overall tree species AGB model by incorporating dummy variables in the stepwise regression process that represent pine and hardwood stands (Rahman *et al.* 2005). However, since individual pine and hardwood regression models were of limited success, the combined regression model will likely also be of mixed quality. One concern here is the presence, typical of the Piedmont, of mixed pine-hardwood stands. Although a judgment call was made regarding the placement of a training point in either the pine or hardwood category, some training points included both species and other types of vegetation species (*e.g.* understory shrub and tree species), which may have led to lower quality regression models given the spectral differences between pines and hardwoods.

6.7 Applicability of basal area and height estimations

A few of the basal area and height regression models that were developed seemed to have high quality (as demonstrated by high R^2 values), and again the higher quality regression models were found with the lower number of training points, and validation tests failed in each case. In the case of basal area models, since the Landsat TM data generally contain spectral reflectance values associated with the upper canopy, the spectral information related to live trees in the intermediate and suppressed canopy classes are not included, although these trees contribute to the basal area computations. Therefore, I was not surprised that a basal area regression model would be difficult to develop. However, the same problem is associated with AGB, which may further explain the mixed results from the AGB model development process. The correlation between tree height and spectral reflectance values would hypothetically be low (particularly for hardwoods); therefore, I was not expecting to develop very good relationships between the Landsat-derived data and tree heights.

6.8 Scientific Contribution from this study

One aspect that may make this study different than others in the published literature is the size of the training points. Here, a single pixel (or weighted average of nearest four pixels) was used as the training point. In other studies (*e.g.* Holmgren *et al*.2000), larger training areas are used, and these could associate more variation in spectral reflectance values with actual forest measurements obtained in the field. In addition, other studies spread their training sites across the landscape in much more widespread manner. If there were any anomalies in the Landsat data over the study area (*e.g.* periodic cloud influence), these were most likely insignificant in other studies, since larger areas were covered. One extension of this work could be to aggregate training points contained within pre-defined management units, to arrive at a average forest condition for each unit. Then, larger management units could be used as training sites, and the forested conditions within them could be associated with a set of pixels whose spectral values may vary over a typical range for the dominant tree species in each unit. My hypothesis, although not tested here, is that this may allow the development of high quality regression models, and models that can also be validated successfully.

CHAPTER 7

Conclusion

Based on a single Landsat TM image, regression models were developed using nine independent variables (TM bands 1-5 and 7, and three vegetation indices) to predict AGB (ton-c per 0.09 ha), total basal area (cm^2 per 0.09 ha) and mean tree height (m per 0.09 ha) in a typical southeast pine-hardwood stands. One assumption was that spectral reflectance values in the independent variables and levels of field measured AGB were, to some degree, correlated, so that high predictive estimation models should be developed, but overall results did not support this assumption.

One major finding in this study was lower numbers of training points may lead to develop higher R^2 valued estimation models. However, the regression models did not result in better accuracy levels than lower R^2 valued models developed based on greater numbers of training points. The lower R^2 valued models may account for variability of AGB levels, as greater numbers of training points have more chance to cover larger areas. Additionally, this tendency was very similar to the results from the basal area and height estimation studies.

In statistics, data in regression analysis are assumed to have a normal distribution, but a normality test did not support that the independent variables derived from six TM bands and three vegetation indices were normally distributed. The non-normal independent variables were applied logarithmic and square root transformations; however, levels of R^2 in the associated models were very similar to regression models developed based on non-transformed independent variables. Also, as another finding, stepwise regression based on Akaike's Information Criterion (AIC) indicated that normality and non-normality of independent variables do not have much impact on the development of high quality models.

Additionally, two different approaches, a strict pixel-based (SPB) and an inversely weighted Euclidean distance (IWED), were performed for the extraction of spectral reflectance values from independent variables. While each field point (training and test points) was determined based on a mapping grade GPS unit, it generally contains locational errors of ± 5-10 m. Also, each field point was not located in the center of each Landsat TM pixel because of they were randomly located. Thus, the IWED approach was hoped to extract reasonably averaged spectral reflectance values to account for the four closest neighbor pixels from each field point; however, the results were very similar to the results based on the SPB approach.

Instead of estimating AGB for the entire study site, AGB was estimated separately for interior forest stands, hardwood stands, and pine stands. In each case, all field points were located at least 30 m away from stand edges; thus, each point should have represented either the pure interior forest stands, the hardwood stands, or the pine stands. However, the results were very similar to the results from the entire study site. Basically, lower numbers of training points tended to develop higher valued R^2 models, but these models showed lower accuracy levels in the accuracy assessment.

Finally, to estimate AGB with reasonable accuracy while using minimum required training points for development of high predictive models, this study established a large set of field points. Unfortunately, levels of R^2 values between independent variables and field measured AGB from training points were very low, as well as the accuracy levels. Consequently, this study did not arrive at a reasonable idea of the appropriate number of minimum training points necessary for the development of highly predictive models. Since few previous studies focused on AGB estimation in small forestlands, it may be necessary to determine the minimum reasonable study area size as well, then correlate the required minimum number of training points to study area size.

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Appendix A

Models were developed using a bootstrapping technique to draw a small set of training point from a larger set of potential training points.

- For the entire study site, these 30 sets were randomly drawn from three hundred potential training points (1-8).
- For the interior forest stands, these 30 sets were randomly drawn from two hundred potential training points (9-14).
- For the hardwood stands, these 30 sets were randomly drawn from ninety-two potential training points (15-18).
- For the pine stands, these 30 sets were randomly drawn from eighty-one potential training points (19-22).

Also, models were developed based on the strict pixel based (SPB) or the inversely weighted Euclidean distance (IWED) approaches. Presented R^2 values of each models were based on independent variables with non-transformation (AGB, BA, and Ht) or with logarithmic or square root transformation (LogAGB, LogBA, LogHt, SqrtAGB, Sqrt,BA, and SqrtHt).

(1) The entire study site based on thirty training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.5401	0.5760	0.5815	0.5867	0.5687	0.5858	0.2525	0.2766	0.2713
2	0.3194	0.3570	0.3342	0.3267	0.3860	0.3348	0.4317	0.5352	0.4721
3	0.6863	0.6927	0.7359	0.5135	0.5627	0.5952	0.5092	0.5113	0.5425
4	0.4825	0.5789	0.5454	0.4039	0.5208	0.4487	0.2979	0.4236	0.3247
5	0.4918	0.4211	0.4570	0.4553	0.3592	0.3918	0.5037	0.4438	0.4345
6	0.3775	0.2813	0.2988	0.4021	0.3135	0.3212	0.5711	0.4875	0.4598
7	0.4094	0.3415	0.3774	0.4404	0.3641	0.4127	0.4265	0.4938	0.4269
8	0.2708	0.2457	0.2547	0.2951	0.3121	0.3063	0.3147	0.3049	0.2963
9	0.5033	0.4572	0.4403	0.4198	0.4169	0.3911	0.3199	0.4095	0.3127
10	0.4016	0.3849	0.3488	0.4052	0.3772	0.3114	0.4900	0.4901	0.3833
11	0.5542	0.5633	0.5602	0.5840	0.5729	0.5801	0.4029	0.4126	0.4085
12	0.2288	0.2897	0.3272	0.2095	0.2437	0.3216	0.3549	0.4280	0.3669
13	0.4894	0.4470	0.4661	0.4136	0.4186	0.4167	0.3696	0.3943	0.3822
14	0.4644	0.2721	0.3574	0.4704	0.2969	0.3824	0.4468	0.3660	0.4079
15	0.3309	0.3750	0.3536	0.4033	0.4468	0.4212	0.5229	0.5404	0.4948
16	0.4431	0.4989	0.4107	0.4502	0.5105	0.4144	0.3872	0.3292	0.2806
17	0.2836	0.2370	0.2122	0.2439	0.2159	0.1461	0.1525	0.3001	0.1377
18	0.7774	0.7036	0.7417	0.6159	0.5352	0.5747	0.5716	0.3201	0.4810
19	0.5590	0.5511	0.5855	0.5641	0.5093	0.5663	0.6000	0.5284	0.5443
20	0.4919	0.4686	0.4799	0.4522	0.4407	0.4445	0.4240	0.4024	0.3784
21	0.4464	0.4331	0.4624	0.4379	0.4522	0.4702	0.5234	0.4900	0.5056
22	0.4795	0.4426	0.4573	0.5205	0.4219	0.4479	0.2523	0.2530	0.2511
23	0.3120	0.3594	0.3754	0.3303	0.3330	0.3754	0.4555	0.4870	0.5025
24	0.4181	0.4158	0.4248	0.4859	0.5008	0.5006	0.4320	0.4389	0.4462
25	0.4437	0.4634	0.4521	0.4079	0.4204	0.4101	0.5066	0.5406	0.5818
26	0.4021	0.4063	0.4036	0.3740	0.3798	0.3740	0.3297	0.2668	0.2969
27	0.3795	0.3732	0.3727	0.3839	0.3858	0.3857	0.2453	0.2921	0.2671
28	0.2792	0.3107	0.3016	0.2119	0.2550	0.2462	0.4155	0.5229	0.4982
29	0.4796	0.5915	0.5324	0.5253	0.6109	0.5525	0.5169	0.5083	0.4038
30	0.4382	0.4187	0.4472	0.4319	0.4240	0.4572	0.6830	0.6794	0.7200
Average	**0.4395**	**0.4319**	**0.4366**	**0.4255**	**0.4185**	**0.4196**	**0.4237**	**0.4292**	**0.4093**
SD	**0.1185**	**0.1223**	**0.1237**	**0.1033**	**0.1032**	**0.1058**	**0.1200**	**0.1032**	**0.1189**

(2) The entire study site based on thirty training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.2772	0.3160	0.2744	0.1567	0.2104	0.1594	0.3520	0.4315	0.3813
2	0.6098	0.5468	0.5649	0.5706	0.4982	0.5265	0.5459	0.5880	0.5331
3	0.5007	0.5166	0.5151	0.3708	0.4171	0.3856	0.2554	0.4397	0.3622
4	0.4507	0.4884	0.4778	0.3981	0.4404	0.4242	0.4013	0.6118	0.4681
5	0.5239	0.4582	0.4727	0.5301	0.4155	0.4316	0.5184	0.3772	0.4392
6	0.4814	0.5337	0.5082	0.4420	0.4892	0.4605	0.2812	0.3728	0.3394
7	0.4914	0.6425	0.5771	0.4845	0.6951	0.6288	0.2551	0.3807	0.3075
8	0.5509	0.6534	0.5884	0.4843	0.6388	0.5630	0.4494	0.4185	0.4187
9	0.3546	0.4091	0.3817	0.4139	0.4395	0.4242	0.4409	0.4789	0.4649
10	0.5270	0.4893	0.5294	0.4867	0.4253	0.5029	0.5167	0.2717	0.4096
11	0.2804	0.2578	0.2648	0.2515	0.2057	0.2366	0.1955	0.1901	0.2359
12	0.5396	0.5479	0.5458	0.5984	0.5868	0.5911	0.3232	0.2436	0.2804
13	0.4759	0.4180	0.4676	0.3833	0.3396	0.4067	0.3787	0.2419	0.3571
14	0.5826	0.5993	0.6114	0.5509	0.5834	0.5878	0.4529	0.6112	0.5500
15	0.4950	0.5015	0.4958	0.4492	0.4613	0.4507	0.5102	0.4813	0.4923
16	0.3725	0.3133	0.3380	0.3636	0.3518	0.3591	0.5442	0.5394	0.5593
17	0.4675	0.5245	0.4831	0.4110	0.5088	0.4459	0.3619	0.4723	0.4542
18	0.4660	0.4327	0.4314	0.4711	0.4344	0.4261	0.4474	0.5148	0.4955
19	0.1320	0.2024	0.1788	0.1364	0.2353	0.1893	0.2420	0.2937	0.2456
20	0.4584	0.4220	0.4529	0.4505	0.3874	0.4356	0.4552	0.4262	0.4319
21	0.3806	0.3975	0.3900	0.3321	0.3507	0.3433	0.2576	0.3059	0.2936
22	0.4099	0.4647	0.4359	0.3069	0.3826	0.3445	0.4143	0.4652	0.4324
23	0.5872	0.5435	0.5580	0.5938	0.4803	0.5302	0.4605	0.5045	0.5152
24	0.5051	0.4921	0.4933	0.4671	0.4957	0.4656	0.5280	0.5118	0.4997
25	0.6749	0.6317	0.6441	0.6183	0.5889	0.5954	0.4188	0.5652	0.5181
26	0.3051	0.3501	0.3578	0.3040	0.3364	0.3378	0.3150	0.3862	0.3358
27	0.3557	0.3264	0.3419	0.3410	0.2871	0.2978	0.5976	0.6173	0.5468
28	0.4935	0.4586	0.4745	0.4138	0.3763	0.3794	0.3112	0.3326	0.3149
29	0.6470	0.6304	0.6259	0.5880	0.5859	0.5625	0.7070	0.6288	0.6121
30	0.4989	0.5108	0.5151	0.4980	0.5149	0.5232	0.5639	0.5042	0.5115
Average	**0.4632**	**0.4693**	**0.4665**	**0.4289**	**0.4388**	**0.4339**	**0.4167**	**0.4402**	**0.4269**
SD	**0.1179**	**0.1142**	**0.1116**	**0.1219**	**0.1221**	**0.1187**	**0.1224**	**0.1221**	**0.1012**

(3) The entire study site based on fifty training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.4172	0.4160	0.3798	0.3620	0.3995	0.2220	0.2915	0.2200	0.2577
2	0.1856	0.1808	0.1278	0.1294	0.1308	0.1272	0.4233	0.2313	0.3158
3	0.3641	0.3520	0.3539	0.3121	0.3164	0.1695	0.2745	0.2212	0.2687
4	0.2234	0.2405	0.2303	0.1727	0.2068	0.1776	0.2733	0.1646	0.2559
5	0.2105	0.1818	0.2014	0.1496	0.0945	0.2026	0.1874	0.2179	0.0682
6	0.5206	0.5389	0.5214	0.4022	0.4669	0.4168	0.4648	0.4863	0.4511
7	0.2069	0.1436	0.1550	0.2508	0.1483	0.2646	0.4410	0.2486	0.4265
8	0.3905	0.3223	0.3415	0.3700	0.3179	0.3319	0.3376	0.3308	0.2863
9	0.4793	0.4771	0.4657	0.4502	0.4753	0.4019	0.3915	0.4718	0.5600
10	0.1652	0.1865	0.1517	0.1482	0.1825	0.2133	0.5213	0.3271	0.3574
11	0.2981	0.2266	0.2372	0.2752	0.1969	0.2832	0.5681	0.3525	0.5713
12	0.4231	0.3817	0.3790	0.3468	0.3185	0.2965	0.6327	0.2568	0.5528
13	0.2992	0.3545	0.3082	0.2533	0.3141	0.2652	0.4477	0.2862	0.4700
14	0.2974	0.3134	0.3058	0.2915	0.3121	0.4056	0.6116	0.3996	0.6052
15	0.2703	0.2593	0.2777	0.2283	0.2170	0.3329	0.4752	0.3022	0.5950
16	0.4040	0.4197	0.4119	0.2813	0.2775	0.2370	0.5239	0.2574	0.5177
17	0.3009	0.3202	0.3161	0.2213	0.2533	0.3313	0.4516	0.3404	0.4825
18	0.3484	0.3067	0.3039	0.2637	0.2612	0.1799	0.3227	0.2073	0.2987
19	0.1996	0.2293	0.2399	0.1637	0.2075	0.3760	0.3858	0.2661	0.4297
20	0.4074	0.4010	0.3911	0.4037	0.3899	0.4119	0.4904	0.4449	0.4959
21	0.0947	0.1126	0.0939	0.0466	0.0769	0.2006	0.2982	0.2753	0.2782
22	0.3020	0.3230	0.3190	0.3226	0.3507	0.2058	0.3665	0.2216	0.3271
23	0.2609	0.3154	0.2971	0.1657	0.2538	0.2569	0.4273	0.3475	0.3786
24	0.2052	0.1873	0.1933	0.1255	0.1416	0.2859	0.3102	0.3073	0.2669
25	0.2965	0.3550	0.3382	0.2207	0.2971	0.3472	0.3261	0.3645	0.3116
26	0.2986	0.2939	0.2887	0.3240	0.3136	0.3946	0.4665	0.4709	0.3429
27	0.4597	0.4399	0.4578	0.4739	0.4331	0.4740	0.5383	0.4421	0.4849
28	0.3052	0.2789	0.2893	0.3032	0.2434	0.2963	0.6434	0.3132	0.6163
29	0.3575	0.3339	0.3521	0.3286	0.3305	0.4293	0.5914	0.4106	0.5909
30	0.2470	0.2612	0.2982	0.1728	0.2354	0.1222	0.4222	0.2272	0.4123
Average	**0.3080**	**0.3051**	**0.3009**	**0.2653**	**0.2721**	**0.2887**	**0.4302**	**0.3138**	**0.4092**
SD	**0.1007**	**0.1008**	**0.1006**	**0.1040**	**0.1029**	**0.0964**	**0.1174**	**0.0899**	**0.1359**

(4) The entire study site based on fifty training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.3781	0.4165	0.3854	0.3013	0.3572	0.3125	0.5039	0.5603	0.5256
2	0.3363	0.2960	0.2959	0.3038	0.2581	0.2475	0.3412	0.3290	0.3069
3	0.2039	0.2997	0.2376	0.1730	0.2373	0.1889	0.4024	0.4624	0.4211
4	0.4691	0.3641	0.3885	0.4201	0.2886	0.3142	0.3640	0.2521	0.2455
5	0.3187	0.3239	0.3223	0.3152	0.3296	0.3229	0.3131	0.3390	0.3168
6	0.3638	0.3101	0.3305	0.3158	0.2847	0.2953	0.3492	0.2353	0.2599
7	0.3364	0.3249	0.3249	0.3173	0.2773	0.2695	0.3366	0.3233	0.2651
8	0.2322	0.2267	0.2191	0.2487	0.2199	0.2198	0.3704	0.2443	0.2606
9	0.3964	0.3080	0.3300	0.3673	0.3058	0.2877	0.3960	0.4558	0.3512
10	0.2293	0.2184	0.2205	0.2339	0.2311	0.2317	0.2233	0.2412	0.2254
11	0.2889	0.2883	0.2862	0.2480	0.2661	0.2551	0.2154	0.3000	0.2456
12	0.4178	0.4205	0.4328	0.3797	0.4024	0.4074	0.5867	0.5372	0.5583
13	0.3239	0.3451	0.3341	0.2835	0.3009	0.2779	0.4515	0.4844	0.4427
14	0.3800	0.3899	0.3962	0.3914	0.4078	0.4007	0.3883	0.3929	0.3788
15	0.2269	0.2035	0.2269	0.2348	0.1841	0.2203	0.3156	0.2610	0.3240
16	0.3979	0.3420	0.3474	0.3705	0.3110	0.3170	0.4351	0.3359	0.2899
17	0.3422	0.3211	0.3263	0.2812	0.2537	0.2587	0.3237	0.3189	0.3219
18	0.2601	0.2406	0.2437	0.2396	0.2369	0.2393	0.2089	0.2008	0.1751
19	0.3030	0.3018	0.3127	0.2527	0.2610	0.2606	0.1853	0.1979	0.1881
20	0.3899	0.4117	0.3696	0.3512	0.3914	0.3418	0.1335	0.2409	0.1912
21	0.3553	0.3474	0.3623	0.3592	0.3920	0.3922	0.5099	0.4735	0.4673
22	0.4280	0.4572	0.4364	0.3468	0.3982	0.3667	0.2035	0.3223	0.2511
23	0.2789	0.3136	0.3031	0.2705	0.3264	0.3119	0.2329	0.4992	0.3831
24	0.2973	0.3270	0.3170	0.2697	0.3327	0.3129	0.2402	0.2629	0.2459
25	0.3249	0.4138	0.4065	0.3155	0.3883	0.3781	0.3534	0.4053	0.3267
26	0.1333	0.1492	0.1203	0.1301	0.1224	0.1112	0.1039	0.1115	0.1137
27	0.4067	0.3225	0.3153	0.3565	0.2704	0.2363	0.2322	0.3505	0.2334
28	0.2680	0.3110	0.2948	0.2465	0.2923	0.2746	0.2894	0.3147	0.3147
29	0.4048	0.4702	0.4459	0.2666	0.3242	0.3046	0.2535	0.3070	0.2825
30	0.5501	0.4616	0.5059	0.5516	0.4573	0.4910	0.5147	0.4826	0.5017
Average	**0.3347**	**0.3309**	**0.3279**	**0.3047**	**0.3036**	**0.2950**	**0.3259**	**0.3414**	**0.3138**
SD	**0.0862**	**0.0775**	**0.0802**	**0.0799**	**0.0742**	**0.0750**	**0.1183**	**0.1119**	**0.1074**

(5) The entire study site based on one hundred training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.3573	0.3663	0.3856	0.3453	0.3113	0.3396	0.2925	0.2058	0.2081
2	0.2527	0.2532	0.2506	0.2318	0.2341	0.2287	0.2398	0.2355	0.2103
3	0.2007	0.1914	0.1974	0.1971	0.1587	0.1757	0.2592	0.1577	0.1837
4	0.2006	0.1792	0.1797	0.1507	0.1313	0.1247	0.2243	0.2547	0.2232
5	0.3269	0.3091	0.3148	0.2485	0.2278	0.2344	0.3015	0.3085	0.3057
6	0.2738	0.2787	0.2789	0.2058	0.2058	0.2015	0.2376	0.2404	0.2281
7	0.3014	0.2769	0.2859	0.2332	0.2209	0.2281	0.1465	0.1295	0.1125
8	0.1531	0.1363	0.1396	0.1462	0.1121	0.1145	0.2105	0.2372	0.2004
9	0.2934	0.3129	0.2818	0.2842	0.3096	0.2806	0.3109	0.3264	0.2865
10	0.2102	0.2065	0.2040	0.1896	0.1847	0.1818	0.2584	0.2574	0.2327
11	0.2678	0.2664	0.2724	0.1965	0.1807	0.1900	0.2118	0.2047	0.1914
12	0.2301	0.2445	0.2365	0.1740	0.1846	0.1779	0.1851	0.1779	0.1714
13	0.2152	0.2111	0.2129	0.2280	0.2121	0.2152	0.2530	0.2645	0.2440
14	0.3310	0.3190	0.3282	0.2791	0.2708	0.2790	0.2510	0.2350	0.2398
15	0.3073	0.3017	0.3059	0.2696	0.2602	0.2631	0.2279	0.2042	0.2057
16	0.2490	0.2551	0.2547	0.2099	0.2033	0.2021	0.2231	0.1849	0.1880
17	0.2022	0.1760	0.1788	0.1314	0.0952	0.0952	0.2223	0.1336	0.1317
18	0.3062	0.3099	0.3100	0.2498	0.2496	0.2511	0.2146	0.2199	0.2120
19	0.2597	0.2576	0.2534	0.2099	0.2072	0.1989	0.2995	0.2840	0.2781
20	0.1949	0.2155	0.1937	0.1585	0.1644	0.1610	0.2131	0.2226	0.1935
21	0.1990	0.1977	0.1914	0.1768	0.1729	0.1639	0.1866	0.1868	0.1792
22	0.2849	0.2153	0.2160	0.2493	0.1718	0.1712	0.1995	0.0909	0.0990
23	0.2907	0.3019	0.2889	0.2492	0.2731	0.2467	0.2672	0.2943	0.2636
24	0.1480	0.1314	0.1376	0.1119	0.0807	0.0895	0.2367	0.2040	0.2102
25	0.2071	0.1793	0.1890	0.1683	0.1487	0.1445	0.1751	0.1752	0.1562
26	0.4187	0.4254	0.4222	0.3551	0.3582	0.3483	0.3533	0.3109	0.2891
27	0.2794	0.2497	0.2465	0.2244	0.2146	0.1972	0.2471	0.1939	0.1711
28	0.3661	0.3876	0.3833	0.3265	0.3495	0.3417	0.2912	0.2789	0.2795
29	0.2263	0.2232	0.2133	0.1819	0.1720	0.1565	0.1989	0.2201	0.1743
30	0.2330	0.2308	0.2305	0.2405	0.2139	0.2174	0.2878	0.2321	0.2363
Average	**0.2596**	**0.2536**	**0.2528**	**0.2208**	**0.2093**	**0.2073**	**0.2409**	**0.2224**	**0.2102**
SD	**0.0636**	**0.0698**	**0.0701**	**0.0598**	**0.0683**	**0.0672**	**0.0458**	**0.0558**	**0.0510**

(6) The entire study site based on one hundred training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.1433	0.1515	0.1559	0.1295	0.1385	0.1411	0.1542	0.1669	0.1615
2	0.1878	0.1895	0.1914	0.1875	0.1953	0.1991	0.1791	0.1813	0.1894
3	0.1699	0.1860	0.1857	0.1099	0.1391	0.1262	0.1228	0.1696	0.1572
4	0.1252	0.1447	0.1316	0.0754	0.0878	0.0741	0.1571	0.1819	0.1442
5	0.1998	0.1839	0.1866	0.1774	0.1474	0.1601	0.1953	0.1971	0.1993
6	0.2054	0.1898	0.2003	0.1947	0.1910	0.1982	0.2706	0.2530	0.2574
7	0.2178	0.2335	0.2245	0.1897	0.1978	0.1912	0.2318	0.2694	0.2486
8	0.3237	0.3362	0.3338	0.2290	0.2538	0.2464	0.2299	0.2889	0.2561
9	0.2887	0.2733	0.2706	0.2726	0.2386	0.2327	0.3243	0.2700	0.2560
10	0.1427	0.1527	0.1500	0.1069	0.1310	0.1230	0.1714	0.1719	0.1690
11	0.2305	0.2575	0.2533	0.1671	0.1853	0.1834	0.1451	0.1717	0.1600
12	0.2525	0.2535	0.2573	0.2651	0.2665	0.2705	0.3353	0.3255	0.3430
13	0.1800	0.1594	0.1621	0.1465	0.1193	0.1200	0.2697	0.2404	0.2118
14	0.1354	0.1470	0.1323	0.1058	0.1109	0.0951	0.1840	0.2168	0.1988
15	0.1798	0.1733	0.1722	0.1380	0.1248	0.1275	0.1799	0.1615	0.1598
16	0.2137	0.2120	0.2120	0.2027	0.1825	0.1892	0.2862	0.2695	0.2480
17	0.1996	0.2152	0.2119	0.1599	0.1775	0.1689	0.2666	0.3052	0.2815
18	0.2139	0.1973	0.2124	0.1559	0.1296	0.1435	0.1619	0.1647	0.1421
19	0.1329	0.1402	0.1355	0.0817	0.0952	0.0884	0.1138	0.1611	0.1335
20	0.2472	0.2210	0.2277	0.1935	0.1764	0.1826	0.2754	0.2897	0.2773
21	0.2147	0.2130	0.2144	0.1409	0.1375	0.1385	0.1909	0.1804	0.1843
22	0.1683	0.1987	0.1841	0.1807	0.1945	0.1800	0.2812	0.2292	0.2313
23	0.1687	0.1731	0.1689	0.1780	0.1761	0.1773	0.2003	0.2036	0.2030
24	0.1795	0.1990	0.1811	0.1709	0.1818	0.1611	0.3184	0.2470	0.2446
25	0.1720	0.1910	0.1820	0.1088	0.1381	0.1223	0.1286	0.1786	0.1453
26	0.2728	0.2927	0.2893	0.1765	0.2240	0.2053	0.1840	0.2559	0.2225
27	0.2728	0.2927	0.2893	0.1765	0.2240	0.2053	0.1840	0.2559	0.2225
28	0.3204	0.2892	0.3128	0.2790	0.2443	0.2605	0.2630	0.2671	0.2627
29	0.2034	0.1718	0.1898	0.2030	0.1601	0.1821	0.2559	0.2109	0.2054
30	0.2564	0.2731	0.2702	0.2135	0.2256	0.2181	0.0996	0.1188	0.1096
Average	**0.2073**	**0.2104**	**0.2096**	**0.1706**	**0.1731**	**0.1704**	**0.2120**	**0.2201**	**0.2075**
SD	**0.0533**	**0.0519**	**0.0539**	**0.0518**	**0.0479**	**0.0494**	**0.0659**	**0.0525**	**0.0537**

(7) The entire study site based on two hundred training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.1800	0.1758	0.1558	0.1345	0.1345	0.1190	0.1364	0.1177	0.0948
2	0.1939	0.1881	0.1873	0.1487	0.1489	0.1443	0.1149	0.1172	0.1081
3	0.1345	0.1340	0.1334	0.0989	0.0965	0.0941	0.1418	0.1371	0.1318
4	0.2072	0.2063	0.1851	0.1460	0.1556	0.1396	0.1661	0.1626	0.1564
5	0.1605	0.1493	0.1505	0.1096	0.1006	0.0975	0.1480	0.1565	0.1355
6	0.2023	0.1873	0.1850	0.1550	0.1334	0.1320	0.1490	0.1248	0.1261
7	0.1996	0.1766	0.1802	0.1559	0.1385	0.1375	0.1259	0.0980	0.0937
8	0.1701	0.1826	0.1735	0.1335	0.1460	0.1394	0.1525	0.1229	0.1256
9	0.1413	0.1441	0.1401	0.1060	0.1061	0.1074	0.1142	0.1007	0.1009
10	0.2043	0.1952	0.1933	0.1291	0.1244	0.1201	0.1255	0.1041	0.1041
11	0.1813	0.1849	0.1737	0.1301	0.1348	0.1295	0.0971	0.1000	0.0869
12	0.2030	0.1955	0.1870	0.1449	0.1406	0.1351	0.1303	0.1151	0.1059
13	0.2289	0.2207	0.2269	0.1724	0.1710	0.1735	0.1338	0.1323	0.1341
14	0.1325	0.1315	0.1311	0.0882	0.0872	0.0908	0.1476	0.1431	0.1425
15	0.1965	0.1940	0.1905	0.1564	0.1543	0.1555	0.1497	0.1404	0.1335
16	0.1646	0.1490	0.1553	0.1195	0.1027	0.1072	0.1480	0.1178	0.1321
17	0.2053	0.1988	0.1960	0.1403	0.1226	0.1211	0.1711	0.1359	0.1294
18	0.1724	0.1485	0.1589	0.1174	0.0971	0.1001	0.1204	0.0955	0.0920
19	0.1759	0.1570	0.1602	0.1106	0.1032	0.1038	0.1224	0.1040	0.1091
20	0.2514	0.2174	0.2237	0.1923	0.1489	0.1540	0.1460	0.1234	0.1279
21	0.1942	0.1851	0.1885	0.1670	0.1429	0.1470	0.2072	0.1681	0.1618
22	0.1816	0.1638	0.1678	0.1433	0.1155	0.1182	0.1547	0.1331	0.1222
23	0.1776	0.1780	0.1766	0.1162	0.1194	0.1188	0.1609	0.1538	0.1532
24	0.1231	0.1206	0.1207	0.0842	0.0825	0.0840	0.0996	0.0928	0.0985
25	0.1522	0.1342	0.1438	0.0999	0.0819	0.0893	0.1064	0.0803	0.0855
26	0.1649	0.1535	0.1584	0.1183	0.1067	0.1091	0.1146	0.0978	0.1005
27	0.1467	0.1477	0.1410	0.1136	0.1102	0.1059	0.1390	0.1384	0.1354
28	0.1878	0.1797	0.1730	0.1244	0.1197	0.1165	0.1249	0.1216	0.1178
29	0.1318	0.1240	0.1132	0.0832	0.0825	0.0738	0.1002	0.1114	0.0851
30	0.2182	0.2172	0.2221	0.2012	0.1875	0.1961	0.2393	0.2011	0.2037
Average	**0.1795**	**0.1713**	**0.1698**	**0.1313**	**0.1232**	**0.1220**	**0.1396**	**0.1249**	**0.1211**
SD	**0.0307**	**0.0288**	**0.0288**	**0.0296**	**0.0272**	**0.0272**	**0.0304**	**0.0262**	**0.0266**

(8) The entire study site based on two hundred training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.1492	0.1489	0.1456	0.1022	0.0981	0.0944	0.1273	0.1294	0.1103
2	0.2095	0.2139	0.2126	0.1778	0.1832	0.1804	0.1676	0.1547	0.1494
3	0.2156	0.2224	0.2188	0.1711	0.1836	0.1759	0.1973	0.1935	0.1858
4	0.2690	0.2682	0.2684	0.2408	0.2425	0.2417	0.2242	0.2230	0.2175
5	0.1599	0.1675	0.1635	0.1255	0.1259	0.1230	0.1534	0.1662	0.1482
6	0.2473	0.2399	0.2466	0.2098	0.1842	0.1967	0.2318	0.1629	0.1780
7	0.2315	0.2394	0.2399	0.1827	0.1888	0.1857	0.1869	0.1996	0.1923
8	0.1388	0.1401	0.1393	0.1111	0.1062	0.1087	0.1538	0.1524	0.1487
9	0.1925	0.2146	0.2067	0.1437	0.1628	0.1527	0.1393	0.1649	0.1461
10	0.1843	0.1910	0.1888	0.1494	0.1536	0.1523	0.1736	0.1806	0.1758
11	0.1329	0.1471	0.1411	0.0954	0.1079	0.1016	0.0988	0.1399	0.1145
12	0.1594	0.1761	0.1697	0.1093	0.1243	0.1162	0.1175	0.1524	0.1312
13	0.1974	0.2140	0.2057	0.1656	0.1732	0.1681	0.2076	0.1967	0.1955
14	0.2527	0.2449	0.2455	0.2035	0.1927	0.1913	0.1864	0.1626	0.1549
15	0.1945	0.1955	0.1964	0.1561	0.1602	0.1607	0.1852	0.1808	0.1801
16	0.1601	0.1678	0.1650	0.1300	0.1326	0.1318	0.1706	0.1694	0.1682
17	0.1976	0.2043	0.2059	0.1547	0.1625	0.1657	0.1981	0.1811	0.1882
18	0.1884	0.1875	0.1863	0.1420	0.1312	0.1299	0.1921	0.1818	0.1576
19	0.1495	0.1539	0.1504	0.1073	0.1070	0.1027	0.1082	0.1193	0.1075
20	0.1803	0.1917	0.1841	0.1415	0.1389	0.1350	0.1446	0.1447	0.1337
21	0.1844	0.1908	0.1872	0.1390	0.1331	0.1308	0.1360	0.1400	0.1297
22	0.2124	0.2258	0.2243	0.1559	0.1693	0.1639	0.1330	0.1435	0.1385
23	0.1664	0.1663	0.1665	0.1245	0.1239	0.1239	0.1571	0.1430	0.1363
24	0.1494	0.1547	0.1542	0.1020	0.1060	0.1076	0.0958	0.1036	0.1008
25	0.1743	0.1905	0.1845	0.1493	0.1723	0.1658	0.1591	0.1817	0.1709
26	0.1882	0.1857	0.1894	0.1452	0.1365	0.1410	0.1472	0.1413	0.1364
27	0.1554	0.1570	0.1551	0.1193	0.1195	0.1178	0.1348	0.1558	0.1451
28	0.1851	0.1958	0.1911	0.1585	0.1722	0.1625	0.1536	0.1855	0.1626
29	0.2362	0.2427	0.2420	0.2074	0.2098	0.2101	0.2084	0.2076	0.1940
30	0.1923	0.1892	0.1894	0.1977	0.1985	0.1900	0.1841	0.1878	0.1898
Average	**0.1885**	**0.1942**	**0.1921**	**0.1506**	**0.1533**	**0.1509**	**0.1624**	**0.1648**	**0.1563**
SD	**0.0346**	**0.0333**	**0.0343**	**0.0364**	**0.0360**	**0.0361**	**0.0357**	**0.0271**	**0.0297**

(9) The interior forest stands based on thirty training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.4293	0.4313	0.4330	0.3677	0.0326	0.3415	0.2526	0.2675	0.2647
2	0.2837	0.2534	0.2568	0.3238	0.0532	0.2419	0.5207	0.5572	0.4823
3	0.4517	0.4775	0.4689	0.4069	0.2159	0.4173	0.5614	0.5952	0.5998
4	0.6527	0.6143	0.6336	0.5733	0.0781	0.5672	0.5831	0.5261	0.5606
5	0.3872	0.4062	0.3952	0.3154	0.0452	0.3196	0.2825	0.2958	0.2882
6	0.6393	0.6057	0.6352	0.5497	0.3174	0.5436	0.5310	0.5395	0.5272
7	0.5192	0.4873	0.4982	0.4642	0.0511	0.4348	0.3287	0.3214	0.3259
8	0.6184	0.5542	0.5854	0.6429	0.1372	0.5721	0.6030	0.3216	0.4477
9	0.4094	0.3846	0.3827	0.3803	0.2747	0.4126	0.6420	0.6460	0.6373
10	0.1988	0.2719	0.2233	0.1563	0.0363	0.1736	0.1939	0.2280	0.2116
11	0.3545	0.3060	0.3298	0.2869	0.0790	0.2445	0.5188	0.5120	0.5255
12	0.4655	0.4215	0.4617	0.4323	0.0403	0.4249	0.4669	0.5179	0.5039
13	0.4863	0.4975	0.4900	0.4155	0.1593	0.4306	0.4965	0.5123	0.5127
14	0.5029	0.5988	0.5648	0.4661	0.0490	0.4940	0.5843	0.5837	0.5680
15	0.5077	0.5395	0.5220	0.4863	0.2413	0.5105	0.3932	0.4555	0.4228
16	0.7175	0.6965	0.7196	0.6807	0.0094	0.6750	0.6710	0.5834	0.6176
17	0.2706	0.2900	0.2320	0.2976	0.0905	0.2755	0.3119	0.4552	0.3114
18	0.4187	0.4881	0.4519	0.3645	0.1186	0.3936	0.4504	0.4661	0.4516
19	0.3340	0.3628	0.3493	0.2965	0.0163	0.3128	0.4449	0.4454	0.4560
20	0.4113	0.3409	0.4010	0.3297	0.0146	0.3205	0.4597	0.4148	0.4219
21	0.3408	0.3264	0.3269	0.2976	0.0572	0.2713	0.2899	0.1940	0.2310
22	0.4733	0.4914	0.4817	0.4728	0.2806	0.4794	0.6842	0.7044	0.7038
23	0.4192	0.3795	0.3678	0.3325	0.0738	0.3037	0.3390	0.2182	0.2779
24	0.4556	0.3982	0.4243	0.4868	0.0041	0.4403	0.4271	0.3611	0.4028
25	0.2658	0.2010	0.2325	0.2354	0.0045	0.2040	0.3679	0.3347	0.3531
26	0.2425	0.2553	0.2576	0.2433	0.0143	0.2625	0.3514	0.2962	0.3204
27	0.4151	0.4259	0.4508	0.4338	0.2058	0.4670	0.5889	0.6588	0.6360
28	0.5965	0.5797	0.5918	0.5869	0.0140	0.5890	0.5364	0.5880	0.5285
29	0.2721	0.2673	0.2683	0.1970	0.0196	0.1966	0.3617	0.3071	0.3283
30	0.5509	0.4729	0.5026	0.4993	0.0191	0.4502	0.6107	0.5746	0.5627
Average	**0.4363**	**0.4275**	**0.4313**	**0.4007**	**0.0918**	**0.3923**	**0.4618**	**0.4494**	**0.4494**
SD	**0.1303**	**0.1264**	**0.1321**	**0.1297**	**0.0933**	**0.1302**	**0.1328**	**0.1440**	**0.1344**

(10) The interior forest stands based on thirty training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.7432	0.7685	0.7447	0.6540	0.7093	0.6874	0.5481	0.5958	0.5715
2	0.4324	0.4780	0.4726	0.3892	0.4421	0.4459	0.3609	0.2458	0.2976
3	0.5051	0.5627	0.5408	0.5138	0.5669	0.5431	0.5384	0.5197	0.4992
4	0.5197	0.5037	0.5121	0.5260	0.5057	0.5149	0.5585	0.5100	0.5223
5	0.4927	0.4104	0.4460	0.4499	0.3863	0.4057	0.2322	0.2285	0.2300
6	0.3987	0.3985	0.3978	0.4129	0.3985	0.4015	0.6621	0.6069	0.6299
7	0.6321	0.5592	0.6137	0.6282	0.6043	0.6318	0.7114	0.7920	0.7723
8	0.4257	0.4386	0.4821	0.4013	0.4213	0.4342	0.4353	0.4217	0.4422
9	0.4612	0.4817	0.4757	0.4342	0.4844	0.4635	0.5741	0.5301	0.5522
10	0.3485	0.3379	0.3507	0.3593	0.3520	0.3594	0.2509	0.2205	0.1840
11	0.3840	0.4690	0.4276	0.3127	0.3817	0.3480	0.1930	0.3150	0.2561
12	0.4395	0.4614	0.4276	0.3790	0.4172	0.3815	0.4040	0.3745	0.3929
13	0.3285	0.3358	0.3303	0.2880	0.3163	0.3046	0.3649	0.3875	0.3803
14	0.3841	0.3939	0.3753	0.3590	0.4336	0.3829	0.3222	0.2705	0.2577
15	0.4215	0.4031	0.4562	0.4237	0.4299	0.4453	0.4253	0.4399	0.4422
16	0.5195	0.5527	0.5438	0.5362	0.5879	0.5635	0.6263	0.7276	0.6508
17	0.4119	0.3902	0.4030	0.3252	0.2567	0.2837	0.4286	0.3724	0.4064
18	0.6014	0.6234	0.6165	0.6041	0.6200	0.6139	0.7032	0.6813	0.6901
19	0.3918	0.4025	0.3971	0.3603	0.3585	0.3558	0.3995	0.4063	0.3794
20	0.2840	0.3218	0.3070	0.2107	0.2549	0.2365	0.2340	0.3161	0.2891
21	0.2979	0.3298	0.3077	0.2759	0.2901	0.2744	0.2860	0.3152	0.2894
22	0.4018	0.4515	0.4285	0.2659	0.3219	0.2919	0.2825	0.3123	0.2982
23	0.4986	0.4611	0.4548	0.4026	0.3636	0.3694	0.1590	0.1061	0.1287
24	0.3983	0.4317	0.4218	0.3896	0.4433	0.4301	0.4081	0.4109	0.4117
25	0.4086	0.3783	0.3829	0.3627	0.3774	0.3708	0.6114	0.6749	0.6668
26	0.5388	0.4793	0.5055	0.4574	0.3488	0.3971	0.5165	0.4998	0.5448
27	0.3237	0.2749	0.2681	0.2841	0.2143	0.1968	0.3677	0.3272	0.2560
28	0.5258	0.5870	0.5616	0.5479	0.5756	0.5470	0.3184	0.2094	0.2304
29	0.4999	0.5217	0.5002	0.3937	0.4476	0.4067	0.7218	0.7310	0.7217
30	0.4879	0.5023	0.5050	0.5177	0.5699	0.5469	0.7085	0.7499	0.7197
Average	**0.4502**	**0.4570**	**0.4552**	**0.4155**	**0.4293**	**0.4211**	**0.4451**	**0.4433**	**0.4371**
SD	**0.1005**	**0.1028**	**0.1022**	**0.1110**	**0.1204**	**0.1188**	**0.1688**	**0.1847**	**0.1821**

(11) The interior forest stands based on fifty training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.2532	0.2541	0.2346	0.2135	0.2066	0.1782	0.3032	0.2219	0.1858
2	0.6149	0.6449	0.6504	0.5497	0.6178	0.5969	0.4260	0.5997	0.4878
3	0.2868	0.2803	0.2825	0.2064	0.2006	0.2062	0.1917	0.1927	0.1917
4	0.1614	0.1866	0.1773	0.1458	0.1504	0.1447	0.1632	0.1397	0.1534
5	0.2805	0.3051	0.3007	0.2404	0.3041	0.2845	0.2801	0.3038	0.2719
6	0.3474	0.3444	0.3442	0.3636	0.3380	0.3327	0.3944	0.3510	0.3067
7	0.3922	0.3770	0.3991	0.3113	0.3283	0.3411	0.3438	0.2692	0.3234
8	0.3182	0.3158	0.3158	0.3185	0.3196	0.3159	0.4346	0.4065	0.4057
9	0.4296	0.4562	0.4464	0.3924	0.4269	0.4105	0.3750	0.4640	0.4208
10	0.4539	0.4961	0.4832	0.4392	0.5034	0.4796	0.3346	0.3370	0.3236
11	0.3880	0.4174	0.4168	0.3771	0.4148	0.4088	0.3038	0.2494	0.2407
12	0.3304	0.3529	0.3430	0.2652	0.2912	0.2817	0.2607	0.2103	0.2311
13	0.2987	0.3262	0.3114	0.2252	0.2467	0.2311	0.3396	0.2987	0.3129
14	0.4266	0.4128	0.4212	0.3902	0.3663	0.3778	0.5312	0.5158	0.5147
15	0.3795	0.4165	0.3969	0.3758	0.4140	0.3835	0.4586	0.4202	0.4163
16	0.5151	0.5123	0.5528	0.4855	0.5405	0.5494	0.3981	0.4872	0.4582
17	0.3694	0.3587	0.3514	0.3580	0.3367	0.3269	0.4927	0.3582	0.3494
18	0.3289	0.3628	0.3491	0.2567	0.3006	0.2775	0.2324	0.2642	0.2240
19	0.4599	0.4451	0.4559	0.3726	0.3663	0.3775	0.2474	0.2808	0.2631
20	0.4261	0.3658	0.3935	0.4141	0.3321	0.3760	0.4838	0.4733	0.4854
21	0.3506	0.3578	0.3542	0.3181	0.3341	0.3264	0.2719	0.2959	0.2896
22	0.3423	0.3333	0.2735	0.2172	0.2542	0.1791	0.2807	0.3210	0.2104
23	0.2991	0.3768	0.3637	0.2140	0.3151	0.2963	0.2814	0.4837	0.4227
24	0.6795	0.4983	0.6413	0.5703	0.4309	0.5617	0.4399	0.3522	0.3409
25	0.3402	0.3422	0.3373	0.3012	0.3106	0.2815	0.3252	0.2919	0.2582
26	0.4339	0.4005	0.4108	0.4064	0.3383	0.3455	0.4332	0.4279	0.3665
27	0.2796	0.3002	0.2879	0.1825	0.1843	0.1732	0.2264	0.1554	0.1640
28	0.4426	0.5342	0.5187	0.4517	0.5686	0.5413	0.4088	0.4371	0.4244
29	0.2124	0.2057	0.2070	0.1775	0.1696	0.1693	0.1684	0.1389	0.1376
30	0.3818	0.4232	0.4055	0.3139	0.3463	0.3311	0.3190	0.3269	0.3201
Average	**0.3741**	**0.3801**	**0.3809**	**0.3285**	**0.3419**	**0.3362**	**0.3383**	**0.3358**	**0.3167**
SD	**0.1075**	**0.0973**	**0.1115**	**0.1098**	**0.1136**	**0.1215**	**0.0987**	**0.1173**	**0.1066**

(12) The interior forest stands based on fifty training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.3027	0.2999	0.3021	0.2240	0.2142	0.2213	0.2352	0.1968	0.2130
2	0.4534	0.4658	0.4645	0.4278	0.4355	0.4304	0.2909	0.3152	0.2857
3	0.5602	0.5878	0.5753	0.4756	0.5218	0.4968	0.3573	0.3242	0.2909
4	0.3421	0.3363	0.3419	0.2863	0.2517	0.2605	0.2816	0.3139	0.2882
5	0.4370	0.4798	0.4653	0.3864	0.4414	0.4212	0.3177	0.2706	0.2676
6	0.3332	0.3474	0.3365	0.3005	0.3041	0.3010	0.3189	0.3271	0.3236
7	0.1940	0.1982	0.1962	0.1494	0.1717	0.1516	0.4459	0.5076	0.4338
8	0.1857	0.2125	0.2040	0.1073	0.1339	0.1215	0.1711	0.1711	0.1535
9	0.3657	0.4229	0.4210	0.3836	0.4677	0.4505	0.5803	0.6236	0.5886
10	0.3995	0.4019	0.3987	0.3266	0.3128	0.3183	0.2751	0.2450	0.2457
11	0.3358	0.3498	0.3433	0.3019	0.3410	0.3234	0.3855	0.4151	0.3972
12	0.4568	0.4527	0.4736	0.4571	0.4710	0.4781	0.4248	0.5437	0.4943
13	0.4908	0.4928	0.4925	0.4265	0.4190	0.4235	0.3920	0.3732	0.3718
14	0.3240	0.3083	0.3066	0.3284	0.2767	0.2933	0.4619	0.4059	0.4320
15	0.3896	0.3025	0.3337	0.3113	0.2140	0.2472	0.4102	0.3229	0.3592
16	0.4480	0.4631	0.4578	0.4694	0.4859	0.4883	0.4244	0.3473	0.3678
17	0.4611	0.4623	0.4613	0.3862	0.3773	0.3779	0.3277	0.3199	0.3153
18	0.5321	0.5225	0.5384	0.4567	0.4671	0.4627	0.4466	0.5344	0.4747
19	0.2687	0.2418	0.2550	0.2037	0.1786	0.1912	0.2608	0.2051	0.2089
20	0.3579	0.3272	0.3388	0.3677	0.3268	0.3341	0.3243	0.3287	0.2931
21	0.2628	0.2674	0.2606	0.2488	0.2392	0.2394	0.2301	0.2257	0.2095
22	0.4366	0.3447	0.4125	0.3802	0.3667	0.3992	0.3485	0.3460	0.3788
23	0.4654	0.4999	0.4895	0.3816	0.4295	0.4122	0.4064	0.4412	0.4199
24	0.4993	0.4813	0.4809	0.4577	0.4292	0.4252	0.3956	0.4078	0.3701
25	0.3205	0.2941	0.3011	0.2634	0.2341	0.2419	0.2103	0.1862	0.1803
26	0.3589	0.3795	0.3722	0.3149	0.3454	0.3352	0.2878	0.2741	0.2631
27	0.3470	0.3822	0.3778	0.2125	0.2755	0.2593	0.2941	0.3220	0.3024
28	0.4561	0.4203	0.4308	0.3629	0.3353	0.3336	0.2891	0.2642	0.2422
29	0.4602	0.5002	0.4942	0.4086	0.4565	0.4479	0.4562	0.4323	0.4321
30	0.4793	0.4970	0.4680	0.4297	0.4393	0.4019	0.4726	0.3904	0.3908
Average	**0.3908**	**0.3914**	**0.3931**	**0.3412**	**0.3454**	**0.3430**	**0.3508**	**0.3460**	**0.3331**
SD	**0.0940**	**0.1002**	**0.0976**	**0.0975**	**0.1080**	**0.1038**	**0.0925**	**0.1106**	**0.1013**

(13) The interior forest stands based on one hundred training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.2921	0.2770	0.2835	0.2271	0.2138	0.2216	0.2345	0.2541	0.2497
2	0.3514	0.3371	0.3211	0.2766	0.2640	0.2690	0.2503	0.2179	0.2355
3	0.2909	0.2135	0.2385	0.2338	0.1773	0.2194	0.1660	0.0941	0.1182
4	0.2765	0.2381	0.2626	0.1989	0.1676	0.1904	0.2778	0.2037	0.2651
5	0.3269	0.2723	0.2714	0.2754	0.2161	0.2415	0.2428	0.1813	0.1822
6	0.3135	0.3205	0.3171	0.2622	0.2668	0.2596	0.2921	0.2813	0.2680
7	0.2903	0.3158	0.3092	0.2140	0.2549	0.2397	0.1926	0.2254	0.1852
8	0.3327	0.3700	0.3649	0.2099	0.2460	0.2304	0.2115	0.2778	0.2088
9	0.2772	0.2172	0.2578	0.1867	0.1568	0.1780	0.1616	0.1223	0.1314
10	0.2980	0.2286	0.2647	0.2210	0.1701	0.2041	0.1308	0.0862	0.1024
11	0.2571	0.2041	0.2498	0.1923	0.1538	0.1910	0.2210	0.1524	0.2274
12	0.2127	0.2166	0.2140	0.1758	0.1775	0.1762	0.1734	0.1664	0.1624
13	0.2330	0.2391	0.2347	0.1936	0.2060	0.1989	0.1268	0.1373	0.1283
14	0.3385	0.3096	0.3250	0.2420	0.2381	0.2436	0.2385	0.2226	0.2325
15	0.3690	0.3708	0.3726	0.2848	0.2911	0.2869	0.2325	0.2258	0.2034
16	0.4107	0.3628	0.4216	0.3230	0.3055	0.3499	0.2727	0.2071	0.2780
17	0.3149	0.2684	0.3069	0.2508	0.2200	0.2523	0.2503	0.2085	0.2489
18	0.3569	0.3136	0.3401	0.2767	0.2453	0.2613	0.2435	0.2180	0.2250
19	0.3349	0.2800	0.3127	0.2331	0.2014	0.2202	0.2346	0.1875	0.1945
20	0.2978	0.2852	0.2853	0.2361	0.2354	0.2413	0.1524	0.1151	0.1360
21	0.3104	0.2992	0.3045	0.2208	0.2286	0.2321	0.1662	0.1601	0.1399
22	0.2836	0.2946	0.2900	0.2109	0.2230	0.2124	0.2726	0.1961	0.1854
23	0.2883	0.3144	0.3092	0.2521	0.3085	0.2902	0.2918	0.3329	0.2908
24	0.3595	0.3291	0.3436	0.2997	0.2740	0.2877	0.2948	0.3089	0.3161
25	0.2673	0.2387	0.2376	0.2003	0.1869	0.1894	0.2004	0.1763	0.1674
26	0.3871	0.3727	0.3900	0.3304	0.3338	0.3417	0.2555	0.2176	0.2481
27	0.2723	0.2309	0.2527	0.1992	0.1704	0.2007	0.2428	0.1902	0.2299
28	0.2548	0.2623	0.2602	0.1978	0.2064	0.1909	0.2534	0.2743	0.1842
29	0.2594	0.2840	0.2757	0.1821	0.2151	0.2027	0.1735	0.1887	0.1792
30	0.2751	0.2368	0.2797	0.2348	0.2151	0.2391	0.2683	0.2246	0.2690
Average	**0.3044**	**0.2834**	**0.2966**	**0.2347**	**0.2256**	**0.2354**	**0.2242**	**0.2018**	**0.2064**
SD	**0.0456**	**0.0507**	**0.0491**	**0.0413**	**0.0470**	**0.0441**	**0.0489**	**0.0592**	**0.0556**

(14) The interior forest stands based on one hundred training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.3405	0.3536	0.3457	0.2574	0.2686	0.2594	0.2936	0.2139	0.2119
2	0.3133	0.3229	0.3158	0.2635	0.2723	0.2602	0.3146	0.2370	0.2208
3	0.3329	0.3570	0.3493	0.2899	0.3174	0.3012	0.3102	0.3710	0.3423
4	0.2919	0.2904	0.2806	0.2469	0.2470	0.2329	0.2467	0.2156	0.1730
5	0.4032	0.3912	0.3966	0.3700	0.3600	0.3596	0.3102	0.2871	0.2715
6	0.3538	0.3797	0.3679	0.2884	0.3265	0.2932	0.2585	0.4027	0.2959
7	0.3270	0.3429	0.3396	0.2814	0.3039	0.2924	0.3833	0.3779	0.3553
8	0.3512	0.3594	0.3540	0.2928	0.3074	0.2970	0.2979	0.2580	0.2603
9	0.2714	0.2801	0.2682	0.1998	0.2182	0.2052	0.2141	0.2606	0.2450
10	0.3091	0.3279	0.3220	0.2575	0.2840	0.2714	0.2096	0.1948	0.1606
11	0.4026	0.3993	0.4050	0.3109	0.3159	0.3131	0.2440	0.2598	0.2574
12	0.4062	0.3811	0.3935	0.3103	0.2994	0.3026	0.2254	0.2359	0.2307
13	0.2692	0.2703	0.2682	0.2113	0.2154	0.2067	0.3155	0.2567	0.2479
14	0.2055	0.2123	0.2122	0.1540	0.1579	0.1513	0.1706	0.1396	0.1458
15	0.2604	0.2509	0.2605	0.1918	0.2025	0.1993	0.1739	0.1731	0.1685
16	0.2704	0.2856	0.2774	0.2289	0.2465	0.2328	0.3674	0.3580	0.3084
17	0.2404	0.2428	0.2517	0.1669	0.1901	0.1828	0.1690	0.2403	0.2146
18	0.1878	0.1826	0.1859	0.1596	0.1473	0.1416	0.2291	0.2256	0.2168
19	0.2864	0.2774	0.2831	0.2121	0.2156	0.2125	0.1985	0.2219	0.2151
20	0.3113	0.3145	0.3122	0.2579	0.2547	0.2533	0.1614	0.1615	0.1592
21	0.3289	0.3331	0.3308	0.2834	0.2853	0.2786	0.2776	0.2362	0.2183
22	0.2649	0.2764	0.2727	0.2000	0.2219	0.2095	0.2200	0.2631	0.2452
23	0.2813	0.2772	0.2781	0.2006	0.1990	0.1981	0.1076	0.0945	0.0970
24	0.3565	0.3447	0.3474	0.2808	0.2491	0.2513	0.3213	0.2797	0.2508
25	0.3515	0.3719	0.3691	0.2427	0.2750	0.2594	0.1269	0.1594	0.1433
26	0.3029	0.2932	0.3014	0.2253	0.2318	0.2267	0.1714	0.1923	0.1851
27	0.3712	0.3691	0.3710	0.3065	0.3288	0.3229	0.1913	0.2217	0.2241
28	0.3235	0.3161	0.3161	0.2833	0.2665	0.2657	0.2739	0.2326	0.2160
29	0.3863	0.3971	0.3962	0.3247	0.3455	0.3320	0.2548	0.2891	0.2423
30	0.3406	0.3337	0.3473	0.2801	0.2851	0.2852	0.2695	0.2938	0.2787
Average	**0.3147**	**0.3178**	**0.3173**	**0.2526**	**0.2613**	**0.2533**	**0.2436**	**0.2451**	**0.2267**
SD	**0.0550**	**0.0553**	**0.0552**	**0.0525**	**0.0539**	**0.0530**	**0.0685**	**0.0699**	**0.0582**

(15) The hardwood stands based on thirty training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.2726	0.2721	0.3263	0.3627	0.3404	0.3935	0.3166	0.3957	0.4191
2	0.1278	0.1280	0.1267	0.1288	0.1301	0.1266	0.3087	0.2840	0.2944
3	0.2608	0.1372	0.2307	0.2281	0.1070	0.1820	0.4456	0.3916	0.4284
4	0.2254	0.3202	0.2796	0.2718	0.3387	0.3112	0.2461	0.3635	0.3176
5	0.1659	0.1726	0.1727	0.1646	0.1622	0.1658	0.4044	0.3961	0.4003
6	0.4651	0.3569	0.4814	0.3898	0.3352	0.4649	0.5297	0.5079	0.5446
7	0.2201	0.1867	0.2299	0.1947	0.1635	0.2187	0.1242	0.1204	0.1766
8	0.6860	0.5743	0.7088	0.7027	0.6351	0.7204	0.5655	0.4769	0.5854
9	0.2631	0.2200	0.2558	0.2991	0.2693	0.2727	0.2589	0.2633	0.2605
10	0.2435	0.2160	0.2432	0.2173	0.2144	0.2151	0.1461	0.1496	0.1481
11	0.4186	0.4436	0.4382	0.3111	0.3453	0.3321	0.2837	0.4480	0.3698
12	0.3222	0.3093	0.3144	0.3172	0.2810	0.2968	0.4141	0.4533	0.4317
13	0.2074	0.2432	0.2005	0.1619	0.1940	0.1473	0.1925	0.2234	0.1794
14	0.2644	0.2349	0.2420	0.2272	0.2139	0.2093	0.2304	0.2760	0.2507
15	0.2569	0.2863	0.2910	0.2083	0.2368	0.2372	0.3053	0.3028	0.3213
16	0.3158	0.4593	0.4095	0.3154	0.4487	0.4015	0.3703	0.4250	0.4161
17	0.2727	0.2504	0.2634	0.2523	0.2269	0.2399	0.2918	0.2560	0.2823
18	0.2649	0.2071	0.2385	0.2141	0.1721	0.1931	0.2669	0.2443	0.2529
19	0.1318	0.1034	0.1291	0.1162	0.0989	0.1175	0.2791	0.3088	0.3611
20	0.1705	0.1986	0.1872	0.2033	0.2314	0.2221	0.3440	0.3305	0.3408
21	0.4988	0.5034	0.5093	0.5702	0.5730	0.5731	0.5774	0.4811	0.5669
22	0.3712	0.3501	0.3184	0.3602	0.3397	0.3374	0.3229	0.3090	0.2876
23	0.3740	0.3493	0.3656	0.3830	0.3736	0.3811	0.4250	0.4573	0.4621
24	0.1513	0.1688	0.2716	0.1730	0.1872	0.2716	0.3726	0.3544	0.4220
25	0.3713	0.3835	0.3829	0.4322	0.4362	0.4412	0.4381	0.4733	0.4447
26	0.2312	0.2878	0.2597	0.2398	0.2669	0.2530	0.2607	0.2670	0.2672
27	0.2883	0.2943	0.2850	0.2928	0.2994	0.2865	0.2192	0.2439	0.2185
28	0.2573	0.1570	0.2655	0.1984	0.1499	0.2162	0.4141	0.3508	0.4182
29	0.2229	0.2637	0.2520	0.2617	0.2514	0.2662	0.1371	0.1288	0.1363
30	0.4001	0.3709	0.3836	0.3594	0.3293	0.3369	0.3121	0.2836	0.2869
Average	**0.2907**	**0.2816**	**0.3021**	**0.2852**	**0.2784**	**0.2944**	**0.3268**	**0.3322**	**0.3431**
SD	**0.1194**	**0.1144**	**0.1207**	**0.1262**	**0.1271**	**0.1319**	**0.1170**	**0.1069**	**0.1189**

(16) The hardwood stands based on thirty training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.1889	0.2094	0.2250	0.1943	0.1944	0.2095	0.3420	0.3469	0.0054
2	0.6490	0.6132	0.6485	0.6252	0.5798	0.6072	0.6013	0.5563	0.2218
3	0.3565	0.3688	0.3597	0.3477	0.3602	0.3645	0.1269	0.1228	0.0074
4	0.2817	0.2567	0.2901	0.3121	0.2771	0.3291	0.2613	0.2088	0.0030
5	0.2112	0.1997	0.3100	0.3500	0.2633	0.3729	0.5941	0.5093	0.0014
6	0.2122	0.2784	0.2932	0.2712	0.3003	0.3098	0.4527	0.3891	0.0122
7	0.3901	0.3776	0.4190	0.3747	0.3529	0.4228	0.3543	0.3288	0.0000
8	0.2493	0.3190	0.2779	0.2741	0.3106	0.2981	0.2003	0.3256	0.0599
9	0.5079	0.4156	0.5580	0.4323	0.3232	0.4488	0.6051	0.5494	0.1316
10	0.3067	0.4016	0.5343	0.4063	0.4403	0.5843	0.4006	0.3909	0.0651
11	0.3388	0.3451	0.2986	0.3120	0.3085	0.2514	0.5339	0.5302	0.0584
12	0.4474	0.4095	0.4774	0.4253	0.3584	0.4293	0.3586	0.3636	0.0002
13	0.3917	0.3199	0.3737	0.3927	0.3276	0.4046	0.5622	0.4721	0.0349
14	0.3015	0.2281	0.2783	0.3003	0.2496	0.2895	0.3575	0.3146	0.0129
15	0.3116	0.2356	0.3351	0.3126	0.2530	0.3373	0.4416	0.4508	0.0029
16	0.4537	0.4132	0.3917	0.4612	0.4295	0.4179	0.3696	0.3692	0.0650
17	0.3934	0.4133	0.3305	0.4361	0.4413	0.3474	0.3949	0.4110	0.1128
18	0.2856	0.2237	0.1246	0.2262	0.2549	0.3238	0.2514	0.2635	0.2325
19	0.1268	0.1850	0.1596	0.2068	0.2424	0.2160	0.4095	0.4327	0.0720
20	0.3528	0.2818	0.2407	0.3222	0.2568	0.2158	0.3801	0.3531	0.0000
21	0.4416	0.3696	0.4302	0.4878	0.3527	0.4549	0.1865	0.3858	0.0344
22	0.4691	0.4720	0.5529	0.4138	0.4219	0.5257	0.4138	0.4564	0.1439
23	0.3068	0.3337	0.3644	0.3364	0.3388	0.3538	0.4913	0.4711	0.0104
24	0.5769	0.5403	0.5639	0.5381	0.5342	0.5371	0.6967	0.7651	0.0332
25	0.5096	0.4963	0.4433	0.4804	0.4680	0.4096	0.6096	0.5863	0.0086
26	0.5096	0.4963	0.4433	0.4804	0.4680	0.4096	0.6096	0.5863	0.0086
27	0.4080	0.4905	0.4462	0.4291	0.4691	0.4371	0.4881	0.4908	0.0649
28	0.3799	0.4815	0.3988	0.4021	0.4796	0.3889	0.6427	0.6765	0.0080
29	0.2226	0.2586	0.2698	0.2269	0.2612	0.2726	0.4973	0.5305	0.0683
30	0.4096	0.4677	0.4749	0.4062	0.4896	0.4799	0.4691	0.4947	0.1161
Average	**0.3664**	**0.3634**	**0.3771**	**0.3728**	**0.3602**	**0.3816**	**0.4367**	**0.4377**	**0.0532**
SD	**0.1206**	**0.1131**	**0.1244**	**0.1013**	**0.1002**	**0.1036**	**0.1445**	**0.1341**	**0.0633**

(17) The hardwood stands based on fifty training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.1292	0.0825	0.1025	0.1052	0.0514	0.0773	0.1496	0.0991	0.1162
2	0.2809	0.2813	0.2864	0.2174	0.2363	0.2269	0.3551	0.2972	0.3986
3	0.2144	0.2054	0.2311	0.2093	0.1942	0.2179	0.1387	0.2029	0.2214
4	0.2198	0.2087	0.2160	0.2018	0.1865	0.1904	0.3010	0.2734	0.2780
5	0.2640	0.1861	0.2620	0.2385	0.1888	0.2207	0.2085	0.2070	0.2423
6	0.1692	0.1810	0.1958	0.1480	0.1653	0.1658	0.2915	0.2991	0.3036
7	0.2240	0.2447	0.2478	0.1893	0.2321	0.2002	0.4206	0.3968	0.4156
8	0.3461	0.3164	0.3467	0.3513	0.2836	0.3310	0.2828	0.2762	0.2891
9	0.2599	0.2617	0.2523	0.1915	0.1983	0.1814	0.2265	0.2670	0.2251
10	0.2156	0.1923	0.2312	0.2227	0.1881	0.2121	0.2637	0.2275	0.2767
11	0.1116	0.1635	0.1690	0.1595	0.2425	0.2089	0.1962	0.3169	0.3592
12	0.3080	0.2481	0.3084	0.3109	0.2312	0.2867	0.3471	0.2763	0.3288
13	0.1763	0.2037	0.2012	0.2400	0.2344	0.2449	0.3720	0.3197	0.3572
14	0.1376	0.1323	0.1921	0.1315	0.1302	0.1688	0.2290	0.1987	0.2605
15	0.2707	0.2861	0.2825	0.2851	0.2976	0.2940	0.2240	0.2255	0.2264
16	0.3746	0.2656	0.4285	0.3948	0.3229	0.4255	0.3896	0.3902	0.4390
17	0.1224	0.1392	0.1854	0.1075	0.1185	0.1553	0.2193	0.2616	0.2475
18	0.2059	0.1662	0.2609	0.1827	0.1961	0.2059	0.2092	0.1426	0.2080
19	0.2766	0.3044	0.3011	0.2859	0.2907	0.2963	0.2606	0.2965	0.2796
20	0.2831	0.2070	0.2826	0.2089	0.1857	0.2039	0.1894	0.1712	0.1785
21	0.2425	0.1532	0.2189	0.2101	0.1554	0.1866	0.3392	0.2712	0.3180
22	0.2340	0.1405	0.2257	0.2186	0.1341	0.1976	0.2471	0.2689	0.2740
23	0.2216	0.1866	0.2196	0.2027	0.2036	0.2021	0.2302	0.2294	0.2227
24	0.3440	0.2897	0.3181	0.3263	0.2596	0.2921	0.2716	0.2857	0.2788
25	0.1815	0.0634	0.1987	0.1367	0.0815	0.1766	0.2066	0.1608	0.3273
26	0.2502	0.2253	0.2616	0.2617	0.2516	0.2646	0.3170	0.3025	0.3158
27	0.3378	0.3167	0.3198	0.3750	0.3649	0.3543	0.3686	0.3934	0.3616
28	0.2456	0.2726	0.3156	0.2439	0.2757	0.2812	0.1994	0.3094	0.2850
29	0.1942	0.1405	0.1897	0.1910	0.1653	0.1774	0.2744	0.2431	0.2403
30	0.2089	0.1935	0.3008	0.2130	0.2162	0.2637	0.3616	0.3344	0.4580
Average	**0.2350**	**0.2086**	**0.2517**	**0.2254**	**0.2094**	**0.2303**	**0.2697**	**0.2648**	**0.2911**
SD	**0.0676**	**0.0669**	**0.0641**	**0.0735**	**0.0695**	**0.0689**	**0.0738**	**0.0709**	**0.0770**

(18) The hardwood stands based on fifty training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.3409	0.3346	0.3405	0.3454	0.3194	0.3339	0.3486	0.3361	0.3437
2	0.2669	0.2637	0.2654	0.2370	0.2303	0.2339	0.3715	0.3234	0.3514
3	0.3699	0.3753	0.3719	0.3923	0.3707	0.3831	0.2786	0.3265	0.3054
4	0.1561	0.2093	0.1731	0.1782	0.2116	0.1891	0.3413	0.3927	0.3741
5	0.1542	0.1429	0.1539	0.2094	0.1832	0.2063	0.1925	0.1643	0.1798
6	0.2174	0.2205	0.2201	0.1728	0.1585	0.1690	0.2606	0.2560	0.2812
7	0.2548	0.2278	0.2355	0.2615	0.2372	0.2502	0.2615	0.2477	0.2546
8	0.2472	0.2681	0.2607	0.1885	0.2043	0.1989	0.3128	0.3323	0.3258
9	0.2792	0.2811	0.2857	0.2992	0.2797	0.2962	0.3623	0.3078	0.3395
10	0.2798	0.4381	0.3491	0.3053	0.3967	0.3451	0.4884	0.5606	0.5504
11	0.3324	0.2911	0.3353	0.2836	0.2121	0.2699	0.4107	0.3299	0.4040
12	0.4044	0.4323	0.4181	0.3728	0.3864	0.3754	0.2777	0.3210	0.3083
13	0.2929	0.2298	0.2641	0.3009	0.2314	0.2703	0.4493	0.4133	0.4291
14	0.2396	0.2039	0.2255	0.2115	0.1832	0.1970	0.2740	0.2290	0.2523
15	0.2887	0.2751	0.2802	0.3104	0.2780	0.2944	0.3432	0.3279	0.3318
16	0.3215	0.2939	0.3094	0.3387	0.3101	0.3249	0.3095	0.3585	0.3266
17	0.4067	0.3860	0.3975	0.4535	0.4240	0.4398	0.3278	0.3237	0.3224
18	0.3057	0.3315	0.3209	0.3116	0.3032	0.3121	0.2962	0.4141	0.3420
19	0.1789	0.2269	0.2163	0.2560	0.2337	0.2611	0.3943	0.3925	0.4451
20	0.3042	0.3554	0.3311	0.2751	0.2864	0.2832	0.4581	0.4607	0.4734
21	0.1825	0.1955	0.1910	0.2056	0.2374	0.2244	0.2215	0.2744	0.2483
22	0.3299	0.4241	0.3954	0.3900	0.4696	0.4489	0.3387	0.4740	0.4039
23	0.3374	0.3310	0.3611	0.3916	0.3528	0.4013	0.4194	0.3902	0.4300
24	0.2471	0.2422	0.2530	0.2063	0.1878	0.2051	0.3201	0.3171	0.3205
25	0.2330	0.2384	0.2400	0.2188	0.2118	0.2167	0.2667	0.3024	0.2839
26	0.2533	0.2333	0.2460	0.2292	0.1999	0.2127	0.3801	0.4576	0.4146
27	0.3667	0.3786	0.3991	0.3828	0.3569	0.3935	0.3667	0.3616	0.3785
28	0.2110	0.2046	0.2085	0.2426	0.2400	0.2439	0.1995	0.2004	0.2080
29	0.2152	0.2106	0.2174	0.2117	0.1994	0.2091	0.2034	0.1973	0.2004
30	0.1802	0.2749	0.2228	0.1942	0.2231	0.2148	0.3642	0.3443	0.3769
Average	**0.2733**	**0.2840**	**0.2830**	**0.2792**	**0.2706**	**0.2801**	**0.3280**	**0.3379**	**0.3402**
SD	**0.0701**	**0.0782**	**0.0734**	**0.0768**	**0.0813**	**0.0794**	**0.0767**	**0.0875**	**0.0837**

(19) The pine stands based on thirty training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.4291	0.2840	0.3041	0.3869	0.2974	0.2700	0.6069	0.5219	0.4923
2	0.3030	0.2549	0.2781	0.2883	0.2773	0.2733	0.5646	0.7036	0.6561
3	0.1732	0.0914	0.1085	0.2511	0.1563	0.1692	0.3576	0.3658	0.3513
4	0.3256	0.2234	0.2251	0.3274	0.2529	0.2338	0.4323	0.3982	0.4102
5	0.3358	0.3256	0.2940	0.4008	0.4157	0.3711	0.5323	0.4713	0.4358
6	0.2296	0.2196	0.1884	0.2145	0.2160	0.1842	0.3575	0.3617	0.3413
7	0.2921	0.3611	0.2979	0.3071	0.4347	0.3207	0.6452	0.6741	0.5738
8	0.3947	0.1782	0.1920	0.3561	0.1659	0.1272	0.4079	0.3505	0.3001
9	0.2474	0.2416	0.2338	0.3637	0.3435	0.3539	0.4989	0.5173	0.5069
10	0.3276	0.1314	0.0745	0.3410	0.1288	0.0764	0.4904	0.4099	0.2651
11	0.3239	0.2994	0.2319	0.2865	0.3041	0.1840	0.4511	0.5796	0.3685
12	0.5542	0.4314	0.4280	0.5515	0.4715	0.4390	0.6561	0.5518	0.4934
13	0.4262	0.2807	0.3467	0.5147	0.4029	0.4342	0.6227	0.6342	0.6087
14	0.3651	0.2976	0.2934	0.4890	0.4457	0.4166	0.5909	0.5555	0.5097
15	0.4876	0.2919	0.3228	0.5312	0.3112	0.3069	0.6433	0.2979	0.3500
16	0.3818	0.1332	0.2435	0.5245	0.1936	0.3044	0.5712	0.4846	0.3389
17	0.2750	0.1592	0.0547	0.3623	0.2463	0.1068	0.5792	0.5817	0.3680
18	0.2957	0.3348	0.2754	0.3380	0.4215	0.3192	0.5232	0.7031	0.5974
19	0.3600	0.4213	0.2937	0.3817	0.4841	0.2921	0.4067	0.5702	0.3417
20	0.3016	0.1743	0.2256	0.3208	0.2028	0.2387	0.2592	0.2326	0.2283
21	0.4880	0.3602	0.3797	0.5009	0.4111	0.3742	0.4104	0.4454	0.3238
22	0.4024	0.4874	0.4679	0.4984	0.5476	0.5436	0.6225	0.7090	0.6731
23	0.4514	0.3640	0.3500	0.5349	0.4320	0.3938	0.6714	0.4883	0.4959
24	0.2456	0.2299	0.1869	0.3972	0.3817	0.3279	0.5671	0.5678	0.5515
25	0.5691	0.2123	0.2545	0.4955	0.2582	0.2008	0.4703	0.5344	0.3190
26	0.4853	0.3374	0.4086	0.5068	0.3683	0.3825	0.6513	0.5709	0.5772
27	0.5210	0.4368	0.4599	0.5844	0.4788	0.4819	0.6188	0.5441	0.4419
28	0.3374	0.5305	0.2768	0.4052	0.5663	0.2389	0.6247	0.6576	0.4027
29	0.3453	0.3091	0.3208	0.3876	0.3412	0.3587	0.5958	0.5396	0.5461
30	0.4790	0.3890	0.4139	0.4775	0.4371	0.3877	0.4882	0.5560	0.3700
Average	**0.3718**	**0.2931**	**0.2810**	**0.4108**	**0.3465**	**0.3037**	**0.5306**	**0.5193**	**0.4413**
SD	**0.1003**	**0.1085**	**0.1030**	**0.0994**	**0.1185**	**0.1129**	**0.1070**	**0.1210**	**0.1202**

(20) The pine stands based on thirty training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.2847	0.2562	0.2538	0.3643	0.3513	0.3377	0.5787	0.6583	0.5940
2	0.4082	0.2459	0.1819	0.4358	0.2405	0.1479	0.4360	0.3942	0.2003
3	0.5207	0.3888	0.4464	0.5632	0.4392	0.4742	0.5747	0.5931	0.5776
4	0.4367	0.4041	0.4234	0.5522	0.5334	0.5490	0.6681	0.6794	0.6688
5	0.2014	0.2850	0.1902	0.2443	0.4086	0.2872	0.3487	0.5610	0.3953
6	0.5066	0.4115	0.3128	0.4700	0.4211	0.3180	0.4431	0.4487	0.3412
7	0.4859	0.3251	0.3292	0.4853	0.3339	0.3225	0.4235	0.3035	0.2895
8	0.3883	0.4315	0.4140	0.4431	0.4936	0.4637	0.6112	0.7308	0.5999
9	0.3314	0.2865	0.2415	0.4556	0.4527	0.3702	0.4736	0.5169	0.4348
10	0.3708	0.3125	0.2400	0.3630	0.3628	0.2497	0.4412	0.5197	0.3509
11	0.3501	0.4847	0.4110	0.3781	0.5919	0.4677	0.5501	0.6913	0.5345
12	0.3927	0.4257	0.4523	0.5433	0.5972	0.6239	0.6746	0.7146	0.7146
13	0.4476	0.3701	0.3697	0.4282	0.3945	0.3615	0.3854	0.3572	0.2980
14	0.3095	0.2398	0.2550	0.4346	0.3645	0.3720	0.6344	0.7044	0.6187
15	0.3098	0.3041	0.2475	0.3665	0.3935	0.2902	0.3453	0.5160	0.3026
16	0.2497	0.2454	0.2249	0.3572	0.3731	0.2784	0.5012	0.7011	0.4924
17	0.5436	0.4828	0.4797	0.6181	0.5217	0.5234	0.6463	0.6165	0.5623
18	0.4064	0.3610	0.3998	0.5235	0.4635	0.4799	0.5569	0.5996	0.5293
19	0.4431	0.3698	0.2650	0.4357	0.3691	0.2611	0.5577	0.5674	0.4342
20	0.3430	0.3465	0.2968	0.3882	0.4090	0.3257	0.5343	0.5652	0.4779
21	0.1832	0.1178	0.0785	0.2549	0.1856	0.1132	0.2710	0.2814	0.1541
22	0.2228	0.2217	0.1971	0.2119	0.2164	0.1775	0.2333	0.2132	0.1928
23	0.5955	0.2487	0.3249	0.6041	0.2143	0.2437	0.5105	0.2362	0.1289
24	0.2966	0.2418	0.2265	0.3685	0.3508	0.3173	0.4487	0.4577	0.3478
25	0.2891	0.2573	0.2770	0.3083	0.2669	0.2974	0.4690	0.4837	0.5717
26	0.4897	0.4706	0.4844	0.5378	0.5324	0.5444	0.6588	0.7650	0.7189
27	0.3458	0.1538	0.1341	0.4632	0.2376	0.1791	0.6582	0.5268	0.4192
28	0.4680	0.3635	0.3147	0.5536	0.5195	0.4147	0.5570	0.7014	0.6226
29	0.5024	0.3996	0.4171	0.5555	0.4880	0.4748	0.4539	0.4336	0.4826
30	0.4122	0.4045	0.4341	0.4428	0.4650	0.4648	0.4089	0.3770	0.3680
Average	**0.3845**	**0.3285**	**0.3108**	**0.4384**	**0.3997**	**0.3577**	**0.5018**	**0.5305**	**0.4474**
SD	**0.1053**	**0.0944**	**0.1077**	**0.1053**	**0.1125**	**0.1284**	**0.1176**	**0.1552**	**0.1645**

(21) The pine stands based on fifty training points with the SPB approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.2624	0.1446	0.1510	0.3059	0.2133	0.1915	0.5160	0.4853	0.4572
2	0.4467	0.1972	0.2328	0.4070	0.2109	0.2065	0.3603	0.3105	0.2538
3	0.2883	0.2652	0.2491	0.3594	0.2969	0.2666	0.5337	0.3522	0.3701
4	0.2757	0.1463	0.1522	0.3150	0.2051	0.1826	0.3683	0.2761	0.2460
5	0.3494	0.1734	0.1532	0.3560	0.2437	0.1727	0.4587	0.3732	0.2741
6	0.2732	0.2375	0.2012	0.3022	0.2684	0.1966	0.4552	0.3227	0.2313
7	0.3453	0.2304	0.2556	0.3905	0.2585	0.2649	0.5063	0.3950	0.3613
8	0.3917	0.2411	0.1819	0.3926	0.2716	0.1579	0.4732	0.3170	0.2359
9	0.2612	0.1096	0.1144	0.2821	0.1434	0.1073	0.3379	0.3440	0.2386
10	0.2601	0.2157	0.2411	0.2895	0.2449	0.2585	0.3858	0.3706	0.3544
11	0.2876	0.1799	0.1749	0.3489	0.2512	0.2048	0.4060	0.2659	0.2147
12	0.2469	0.1377	0.1510	0.2833	0.1914	0.1563	0.4266	0.3766	0.2550
13	0.2966	0.3293	0.3087	0.3141	0.3530	0.3176	0.3990	0.4879	0.3917
14	0.2441	0.3112	0.2587	0.2932	0.3608	0.2814	0.5076	0.5097	0.4337
15	0.2651	0.2147	0.1823	0.2712	0.2804	0.1982	0.3919	0.3949	0.2525
16	0.3198	0.2278	0.2153	0.3208	0.2432	0.1953	0.4755	0.3337	0.3303
17	0.4141	0.2246	0.2466	0.4319	0.2380	0.2410	0.4899	0.3302	0.3129
18	0.2925	0.2820	0.2594	0.3608	0.3620	0.3177	0.4099	0.4015	0.3334
19	0.1696	0.0801	0.0949	0.1725	0.0872	0.0794	0.3372	0.2411	0.1960
20	0.2996	0.1194	0.1781	0.3205	0.1407	0.1658	0.4635	0.4387	0.3237
21	0.3764	0.2954	0.2959	0.4173	0.3834	0.3431	0.4819	0.5290	0.4351
22	0.3804	0.2703	0.2989	0.4111	0.3002	0.3033	0.4570	0.4013	0.3830
23	0.3360	0.2634	0.2406	0.3264	0.3117	0.2225	0.4001	0.4409	0.2629
24	0.3191	0.2565	0.2989	0.4402	0.3715	0.3965	0.5176	0.5242	0.5115
25	0.3168	0.1847	0.2198	0.3154	0.2039	0.1987	0.4605	0.3299	0.3474
26	0.2634	0.0877	0.1116	0.2821	0.1069	0.1004	0.3895	0.2411	0.1836
27	0.4289	0.2771	0.2990	0.4701	0.3251	0.2865	0.5075	0.5144	0.3573
28	0.2766	0.1496	0.1243	0.3510	0.2191	0.1557	0.4652	0.3059	0.2489
29	0.3827	0.2743	0.2608	0.4295	0.3345	0.2637	0.4172	0.3749	0.2362
30	0.2010	0.1604	0.1150	0.2309	0.1797	0.1040	0.4119	0.3768	0.2568
Average	**0.3090**	**0.2096**	**0.2089**	**0.3397**	**0.2534**	**0.2179**	**0.4404**	**0.3788**	**0.3096**
SD	**0.0657**	**0.0677**	**0.0647**	**0.0670**	**0.0783**	**0.0767**	**0.0558**	**0.0827**	**0.0835**

(22) The pine stands based on fifty training points with the IWED approach

	AGB	LogAGB	SqrtAGB	BA	LogBA	SqrtBA	Ht	LogHt	SqrtHt
1	0.3109	0.2406	0.3068	0.4088	0.3216	0.3731	0.5082	0.3825	0.3790
2	0.2775	0.1643	0.1587	0.3198	0.2167	0.1670	0.3925	0.3249	0.1551
3	0.3324	0.2153	0.2015	0.3676	0.2600	0.2206	0.4376	0.2972	0.2198
4	0.2833	0.2184	0.1602	0.3441	0.3090	0.1993	0.4497	0.4841	0.2872
5	0.2664	0.1884	0.1460	0.2949	0.2438	0.1735	0.4460	0.4364	0.2919
6	0.3163	0.2154	0.1732	0.3914	0.2910	0.2215	0.3559	0.2244	0.1669
7	0.3131	0.2042	0.2300	0.3481	0.2490	0.2600	0.3971	0.3690	0.3625
8	0.2742	0.1796	0.2273	0.3498	0.2472	0.2824	0.4752	0.3811	0.3678
9	0.2925	0.1921	0.2038	0.3522	0.2414	0.2258	0.3995	0.3106	0.2663
10	0.3387	0.2875	0.2866	0.4059	0.3667	0.3413	0.6063	0.5381	0.4653
11	0.3240	0.2533	0.2552	0.3579	0.2824	0.2741	0.5589	0.4198	0.4029
12	0.3363	0.2963	0.2664	0.3661	0.3527	0.2948	0.4421	0.5205	0.3965
13	0.3315	0.1874	0.1444	0.3823	0.2064	0.1484	0.5335	0.2830	0.2368
14	0.2605	0.1762	0.1601	0.2893	0.2265	0.1834	0.3693	0.2713	0.2076
15	0.3103	0.2521	0.2381	0.3123	0.2618	0.2331	0.4067	0.3387	0.3145
16	0.2694	0.2208	0.2157	0.3086	0.2896	0.2760	0.4253	0.4500	0.4147
17	0.3421	0.2813	0.3107	0.3800	0.3135	0.3348	0.5094	0.4636	0.4644
18	0.3577	0.2903	0.2387	0.4359	0.3785	0.2904	0.4989	0.4980	0.3426
19	0.3461	0.1640	0.1725	0.3770	0.2004	0.1587	0.3918	0.3376	0.1732
20	0.2394	0.2215	0.1810	0.2512	0.2875	0.2122	0.2546	0.4036	0.2432
21	0.3229	0.2172	0.2178	0.3625	0.2716	0.2469	0.5171	0.4935	0.4177
22	0.3192	0.2653	0.2414	0.3520	0.3430	0.2907	0.4822	0.4476	0.4188
23	0.3756	0.3388	0.3272	0.4521	0.4268	0.3984	0.5589	0.4934	0.4591
24	0.1942	0.0938	0.0639	0.2368	0.1942	0.1240	0.2989	0.3478	0.2476
25	0.2813	0.2263	0.2433	0.3300	0.2688	0.2727	0.5011	0.5049	0.4192
26	0.1772	0.0982	0.1117	0.2011	0.1247	0.1161	0.3230	0.1960	0.1660
27	0.3679	0.3191	0.3182	0.4201	0.3823	0.3689	0.4829	0.4599	0.4346
28	0.2550	0.1698	0.1523	0.3159	0.2384	0.1980	0.5187	0.3930	0.3246
29	0.2645	0.2294	0.1900	0.3243	0.2997	0.2415	0.4257	0.3633	0.3033
30	0.3640	0.3194	0.3362	0.4171	0.3611	0.3708	0.4347	0.3538	0.3454
Average	**0.3015**	**0.2242**	**0.2160**	**0.3485**	**0.2819**	**0.2500**	**0.4467**	**0.3929**	**0.3231**
SD	**0.0482**	**0.0597**	**0.0669**	**0.0577**	**0.0662**	**0.0763**	**0.0803**	**0.0898**	**0.0975**

Appendix B

The best combination of independent variables for above ground biomass (AGB), basal area, and height estimation based on Akaike's Information Criterion (AIC). Both best and worst regression model were presented for 22 different conditions (*e.g.* estimation model for the entire study site based on SPB approach with thirty, and fifty training points). The order of selected independent variables their importance in the development of the regression model.

(1) The entire study site based on SPB approach with 30 training points

Dependent variable	Selected independent variables	Model R^2
AGB	MVI7 / B1 / B2 / B7 / B4 / NDVI	0.7039
Basal area	MVI7 / B1 / B7 / B4 / B2 / NDVI	0.5445
Height	B2 / B5 / MVI5 / B7 / B4 / MVI7	0.6576
AGB	B2	0.0371
Basal area	B5	0.0191
Height	NDVI	0.0514

(2) The entire study site based on IWED approach with 30 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B1 / B3	0.4076
Basal area	B1 / B3	0.3721
Height	B4 / MVI5 / B1 / B2	0.5931
AGB	B1	0.0406
Basal area	B1	0.0444
Height	B5	0.0637

(3) The interior forest stands based on SPB approach with 30 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B5 / B2 / B3 / B1	0.5379
Basal area	B5 / B2 / B3 / B1	0.4393
Height	MVI7 / B2 / B1 / MVI5	0.6244
AGB	B4	0.1026
Basal area	B5	0.0309
Height	NDVI	0.0828

(4) The interior forest stands based on IWED approach with 30 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4 / MVI7 / B1 / B2 / B3 / NDVI	0.6889
Basal area	B4 / MVI7 / B1 / B3 / B2 / NDVI	0.6368
Height	B5	0.6467
AGB	B4	0.2044
Basal area	B4	0.1163
Height	NDVI	0.0287

(5) The hardwood stands based on SPB approach with 30 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4 / NDVI / B1 / MVI7 / B3 / B7	0.5937
Basal area	B3 / B1 / B4 / NDVI / MVI7 / B7	0.6542
Height	B7	0.1770
AGB	MVI7	0.0417
Basal area	B7	0.0483
Height	MVI7	0.0350

(6) The hardwood stands based on IWED approach with 30 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B1 / B5 / B7 / B4 / MVI5 / MVI7	0.6271
Basal area	MVI7 / MVI5 / B1	0.4924
Height	B3 / B1 / B2 / MVI5 / B4 / NDVI	0.5198
AGB	B2	0.0202
Basal area	B7	0.0945
Height	NDVI	0.0778

(7) The pine stands based on SPB approach with 30 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B2 / B5	0.2202
Basal area	B3 / B5 / B7 / NDVI / MVI5 / B4	0.5797
Height	B2 / B3 / B1	0.2668
AGB	B7	0.0175
Basal area	B5	0.0375
Height	B2 / B7	0.1533

(8) The pine stands based on IWED approach with 30 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B2 / B1 / MVI5 /	0.2178
Basal area	B2 / B3 / MVI5 / B7 / B4 / B5	0.6012
Height	B5	0.5616
AGB	B2	0.0443
Basal area	B5	0.1394
Height	MVI5	0.1474

(9) The entire study site based on SPB approach with 50 training points

Dependent variable	Selected independent variables	Model R^2
AGB	NDVI / MVI7 / MVI5 / B1 / B4 / B3	0.5006
Basal area	B2 / B3 / NDVI / B7 / MVI7 / B1	0.4260
Height	B2 / B5	0.2483
AGB	MVI5	0.0721
Basal area	MVI5	0.0235
Height	MVI5	0.1702

(10) The entire study site based on IWED approach with 50 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4 / MVI7 / MVI5 / B3 / NDVI / B5	0.4122
Basal area	B4 / MVI7 / B7 / MVI5 / B5 / NDVI	0.5278
Height	MVI7 / MVI5 / NDVI / B4 / B5 / B3	0.5639
AGB	B4	0.0250
Basal area	B2	0.0142
Height	B5	0.0185

(11) The interior forest stands based on SPB approach with 50 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4 / MVI5 / NDVI / B5 / B3 / B1	0.6613
Basal area	B4 / NDVI / MVI5 / B3 / B5 / B1	0.5427
Height	B5 / B3 / MVI7 / B7 / NDVI / MVI5	0.5271
AGB	B3	0.1386
Basal area	B7	0.1224
Height	B3	0.0441

(12) The interior forest stands based on IWED approach with 50 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4 / B2 / NDVI	0.5363
Basal area	B4 / B2 / NDVI	0.4426
Height	B4 / B3 / MVI5 / MVI7 / B1	0.5541
AGB	B4	0.1577
Basal area	B4 / B2 / NDVI	0.0957
Height	B5	0.0807

(13) The hardwood stands based on SPB approach with 50 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B1	0.1267
Basal area	B3	0.1328
Height	MVI5	0.2487
AGB	B3	0.0567
Basal area	B2	0.0349
Height	B2	0.0363

(14) The hardwood stands based on IWED approach with 50 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B3 / B5 / B7 / B4 / NDVI / B1	0.4027
Basal area	B3 / B1 / B7 / B5 / B4 / NDVI	0.2565
Height	MVI7 / B1 / B3 / B4 / NDVI / B5	0.4490
AGB	B1	0.0432
Basal area	MVI5 / B2	0.1026
Height	B2	0.0094

(15) The pine stands based on SPB approach with 50 training points

Dependent variable	Selected independent variables	Model R^2
AGB	MVI5 / NDVI / B5 / B3 / B4 / B1	0.4384
Basal area	B2 / B5 / B1 / MVI5 / NDVI / B3	0.3960
Height	B2 / B3 / B1	0.2439
AGB	B2	0.0039
Basal area	MVI5	0.0187
Height	NDVI / MVI7	0.1037

(16) The pine stands based on IWED approach with 50 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B2 / B1 / MVI5	0.2028
Basal area	B2 / B1 / MVI5	0.2272
Height	B5 / B7 / MVI5	0.3457
AGB	B7	0.0143
Basal area	B7	0.0001
Height	B5	0.0720

(17) The entire study site based on SPB approach with 100 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4 / B2 / MVI5 / B7 / MVI7 / B1	0.4110
Basal area	B4 / B2 / MVI5 / B7 / MVI7 / B1	0.3525
Height	B4 / B2 / NDVI / B3 / B7 / MVI5	0.3082
AGB	B4	0.0969
Basal area	B4	0.0383
Height	B4	0.0871

(18) The entire study site based on IWED approach with 100 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4	0.1605
Basal area	NDVI	0.0965
Height	B4 / B2 / MVI5	0.1714
AGB	NDVI / MVI5 / MVI7	0.1121
Basal area	B3	0.0412
Height	B5 / B1	0.0148

(19) The interior forest stands based on SPB approach with 100 training points

Dependent variable	Selected independent variables	Model R^2
AGB	NDVI / B2 / B4 / B3 / B5 / MVI5	0.3596
Basal area	NDVI / B2 / B4 / B3 / MVI7 / B5	0.3178
Height	B4 / MVI7 / B1	0.2144
AGB	NDVI	0.1643
Basal area	B4	0.1174
Height	NDVI / MVI5	0.1085

(20) The interior forest stands based on IWED approach with 100 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4 / B3 / NDVI / B1 / B5 / MVI5	0.4022
Basal area	NDVI / MVI5 / MVI7	0.2944
Height	B4 / M5 / M7 / B1	0.3312
AGB	NDVI	0.1365
Basal area	B4 / B2 / MVI5	0.1368
Height	B2 / B5	0.0719

(21) The entire study site based on SPB approach with 200 training points

Dependent variable	Selected independent variables	Model R^2
AGB	B4 / B7 / MVI7	0.1934
Basal area	B4 / B1 / MVI5 / B7 / B2 / B3	0.1890
Height	B4 / MVI5 / B1	0.1636
AGB	NDVI	0.0949
Basal area	B4	0.0443
Height	B4	0.0688

(22) The entire study site based on IWED approach with 200 training points

Dependent variable	Selected independent variables	Model R^2
AGB	NDVI / B4 / B3 / B1 / B5 / B7	0.2592
Basal area	NDVI / MVI5 / B1 / B4 / B7 / MVI7	0.2364
Height	B4 / B2 / MVI5 / B7 / B1 / B5	0.1921
AGB	B4	0.1052
Basal area	B4	0.0598
Height	B4 / B5 / B2	0.0858

Appendix C

The normality test in independent variables based on Kolmogrov-Smirnov test values. The cyan highlight indicated the set of independent variables used to develop the best regression model among 30 different sets of thirty randomly drawn training points in the entire study site. The yellow highlight indicated the set of independent variables used to develop the worst regression model among 30 different sets of thirty randomly drawn training points in the entire study site. P-values smaller than 0.01 are used to reject the assumption of normality.

	R^2			p-value								
#	**AGB**	**BA**	**Ht**	**Band 1**	**Band 2**	**Band 3**	**Band 4**	**Band 5**	**Band 7**	**NDVI**	**MVI5**	**MVI7**
1	0.5401	0.5867	0.2525	< 0.0100	< 0.0100	< 0.0100	0.0784	< 0.0100	0.0194	< 0.0100	0.0933	0.0105
2	0.3194	0.3267	0.4317	< 0.0100	< 0.0100	< 0.0100	0.1383	> 0.1500	< 0.0100	< 0.0100	< 0.0100	< 0.0100
3	0.6863	0.5135	0.5092	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	< 0.0100	< 0.0100	< 0.0100	< 0.0100
4	0.4825	0.4039	0.2979	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	0.0729	0.0138	< 0.0100	< 0.0100
5	0.4918	0.4553	0.5037	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	0.0329	> 0.1500	0.0968	< 0.0100
6	0.3775	0.4021	0.5711	< 0.0100	< 0.0100	0.0271	> 0.1500	0.0648	0.02	> 0.1500	< 0.0100	< 0.0100
7	0.4094	0.4404	0.4265	< 0.0100	< 0.0100	< 0.0100	0.1175	> 0.1500	0.0737	> 0.1500	< 0.0100	< 0.0100
8	0.2708	0.2951	0.3147	< 0.0100	< 0.0100	< 0.0100	> 0.1500	0.1365	< 0.0100	> 0.1500	0.0241	< 0.0100
9	0.5033	0.4198	0.3199	< 0.0100	< 0.0100	< 0.0100	> 0.1500	0.0462	< 0.0100	> 0.1500	0.0941	> 0.1500
10	0.4016	0.4052	0.4900	< 0.0100	< 0.0100	< 0.0100	0.1136	> 0.1500	< 0.0100	< 0.0100	< 0.0100	< 0.0100
11	0.5542	0.5840	0.4029	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	< 0.0100	> 0.1500	> 0.1500	0.0364
12	**0.2288**	**0.2095**	**0.3549**	**< 0.0100**	**< 0.0100**	**0.0202**	**> 0.1500**	**< 0.0100**	**< 0.0100**	**0.0746**	**0.0501**	**0.0883**
13	0.4894	0.4136	0.3696	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	0.0102	< 0.0100	< 0.0100	< 0.0100
14	0.4644	0.4704	0.4468	< 0.0100	< 0.0100	0.0219	0.0389	0.0749	< 0.0100	0.0474	0.0563	0.0189
15	0.3309	0.4033	0.5229	< 0.0100	< 0.0100	< 0.0100	0.0749	> 0.1500	< 0.0100	0.0949	0.0949	0.0324
16	0.4431	0.4502	0.3872	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	> 0.1500	< 0.0100	< 0.0100	< 0.0100
17	0.2836	0.2439	0.1525	< 0.0100	< 0.0100	< 0.0100	> 0.1500	< 0.0100	< 0.0100	> 0.1500	0.0394	> 0.1500
18	**0.7774**	**0.6159**	**0.5716**	**< 0.0100**	**< 0.0100**	**0.0205**	**> 0.1500**	**0.0481**	**< 0.0100**	**0.0256**	**< 0.0100**	**< 0.0100**
19	0.5590	0.5641	0.6000	< 0.0100	< 0.0100	0.0103	> 0.1500	> 0.1500	0.021	< 0.0100	< 0.0100	< 0.0100
20	0.4919	0.4522	0.4240	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	< 0.0100	0.0938	< 0.0100	0.0341
21	0.4464	0.4379	0.5234	< 0.0100	< 0.0100	< 0.0100	0.0786	> 0.1500	< 0.0100	< 0.0100	< 0.0100	< 0.0100
22	0.4795	0.5205	0.2523	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	< 0.0100	0.0763	0.0678	0.0519
23	0.3120	0.3303	0.4555	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	0.0173	0.1267	> 0.1500	0.0174
24	0.4181	0.4859	0.4320	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	< 0.0100	0.1074	0.0147	< 0.0100
25	0.4437	0.4079	0.5066	< 0.0100	< 0.0100	< 0.0100	> 0.1500	0.1382	< 0.0100	> 0.1500	< 0.0100	< 0.0100
26	0.4021	0.3740	0.3297	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	0.0281	0.0118	0.0173	0.015
27	0.3795	0.3839	0.2453	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	< 0.0100	> 0.1500	0.0964	0.0824
28	0.2792	0.2119	0.4155	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	0.1004	0.0216	0.087	0.0252
29	0.4796	0.5253	0.5169	< 0.0100	< 0.0100	< 0.0100	> 0.1500	> 0.1500	0.0136	< 0.0100	0.0436	0.0843
30	0.4382	0.4319	0.6830	< 0.0100	< 0.0100	< 0.0100	0.1093	> 0.1500	< 0.0100	0.0535	< 0.0100	< 0.0100
Average	**0.4395**	**0.4255**	**0.4237**									
SD	**0.1185**	**0.1033**	**0.1200**									