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The complicated forest stand structure and associated abundant tree species in the Amazon often induce difficulty in estimating aboveground biomass (AGB) using remotely sensed data. This paper explores AGB estimation using Landsat Thematic Mapper (TM) data in the eastern and western Brazilian Amazon, and discusses the impacts of forest stand structure on AGB estimation. Estimating AGB is still a challenging task, especially for the sites with complicated biophysical environments. The TM spectral responses are more suitable for AGB estimation in the sites with relatively simple forest stand structure than for the sites with complicated forest stand structure. Conversely, textures appear more important than spectral responses in AGB estimation in the sites with complicated forest stand structure. A combination of spectral responses and textures improves AGB estimation performance. Different study areas having various biophysical conditions affect AGB estimation performance.

1. Introduction

The Brazilian Amazon contains the largest continuous moist tropical forest in the world. Its vast areas of tropical forest represent a potentially large source of carbon/greenhouse gas emissions if deforested. Since the 1970s, road-building, logging, agricultural and cattle-raising expansion have resulted in high deforestation rates and make Brazil become the world's fourth major contributor of carbon to the atmosphere. In the overall Amazon basin, about 20–50% deforested areas are in certain stages of successional forests (Moran *et al*. 1994, Skole *et al*. 1994, Lucas *et al*. 2000, Roberts *et al*. 2002). Accurate delineation of successional and mature forest biomass distribution becomes considerably significant in reducing the uncertainty of carbon emission and sequestration, understanding their roles in influencing soil fertility and land degradation or restoration, and understanding the roles in environmental processes and sustainability (Foody 2003).

Aboveground biomass (AGB) is related to many important components, such as carbon cycles, soil nutrient allocations, fuel accumulation, and habitat environments in terrestrial ecosystems. The AGB governs the potential carbon emission that could be released to the atmosphere due to deforestation and change of regional AGB is associated with changes in climate and ecosystem. Hence, the AGB estimation using remotely sensed data has obtained increasing interests in the past decade. Most previous research on AGB estimation is for coniferous forests (Ardo 1992, Wu and Strahler 1994, Trotter *et al*. 1997, Zheng *et al*. 2004) because of its relatively simple forest stand structure and tree species composition. In moist tropical forests, the study of AGB estimation is more problematic because of its complicated stand structure and abundant species composition (Lucas *et al*. 1998, Nelson *et al*. 2000,

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Steininger 2000, Foody *et al.* 2001, 2003, Lu and Batistella (in press)). The complexity of natural vegetation results in highly variable standing stocks of AGB and an even more variable rate of AGB accumulation following a deforestation event. In general, the AGB can be (1) directly estimated using remotely sensed data with different approaches, such as multiple regression analysis, K nearest-neighbour, and neural network (Roy and Ravan 1996, Nelson *et al.* 2000, Steininger 2000, Foody *et al.* 2003, Zheng *et al.* 2004), and (2) indirectly estimated from canopy parameters, such as crown diameter, which are first derived from remote sensed data using multiple regression analysis or different canopy reflectance models (Wu and Strahler 1994, Woodcock *et al.* 1997, Phua and Saito 2003, Popescu *et al.* 2003).

Although much previous research on AGB estimation has explored the tropical regions based on Landsat Thematic Mapper (TM) (Sader *et al.* 1989, Lucas *et al.* 1998, Boyd *et al.* 1999, Nelson *et al.* 2000, Steininger 2000, Foody *et al.* 2001, 2003) or synthetic aperture radar (SAR) data (Rignot *et al.* 1995, Luckman *et al.* 1997, 1998, Santos *et al.* 2002, 2003), research has shown the difficulty of AGB estimation based on purely spectral responses from optical sensor data or backscatters from SAR data. Lucas *et al.* (2004) reviewed SAR data for AGB estimation in tropical forests and indicated the difficulty and data saturation problem in AGB estimation. Because time-series Landsat data are readily available, Landsat TM/ETM+ (Enhanced Thematic Mapper Plus) have become the most common data for AGB estimation. Hence, this paper will only focus on exploration of TM data in AGB estimation in different biophysical environments in the Brazilian Amazon. Much previous research for AGB estimation only used spectral responses (Lucas *et al.* 1998, Nelson *et al.* 2000, Steininger 2000, Foody *et al.* 2001, 2003). The role of textures in improving AGB estimation performance has not been examined yet. However, previous research has shown that textures are helpful in improving land cover or vegetation classification (Franklin and Peddle 1989, Marceau *et al.* 1990, Augusteijn *et al.* 1995, Karathanassi *et al.* 2000, Franklin *et al.* 2001, Podest and Saatchi 2002, Zhang *et al.* 2004) and many texture measures have been developed. Of the many texture measures, the grey-level co-occurrence matrix (GLCM) may be the most common (Marceau *et al.* 1990, Smith *et al.* 2002, Zhang *et al.* 2003). It can be assumed that textures are also useful in improving AGB estimation performance. The critical step is how to identify the suitable textures that can effectively extract AGB information from the selected images. In practice, selection of suitable textures is still a challenging task because textures vary with the characteristics of the landscape under investigation and the images used. This paper aims to explore (1) the role of textures in improving AGB estimation performance through incorporation of spectral responses and textures in the selected study areas in the Amazon basin, and (2) impacts of different forest stand structures on AGB estimation performance.

2. Study areas

Three study areas in the eastern Brazilian Amazon (Altamira, Bragantina, and Ponta de Pedras in Para) and one study area in western Brazilian Amazon (Machadinho d'Oeste in Rondonia) were selected for this research (figure 1). The colour composites with TM bands 4, 5, and 3 (as red, green, and blue) in figure 1 demonstrate that the selected four study areas have significantly different land cover patterns and footprints of land use histories. In Altamira, deforestation began in the

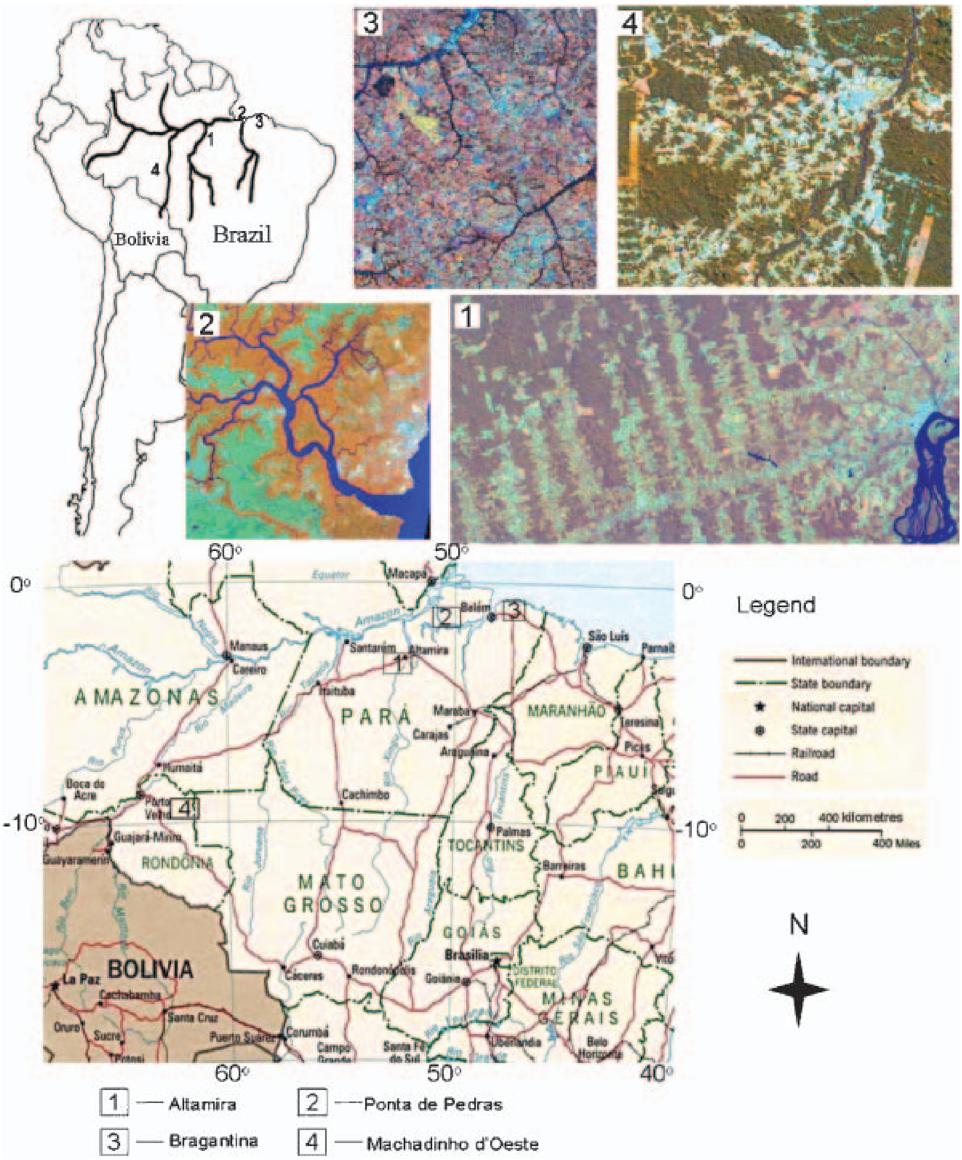

Figure 1. Location of selected study areas in the Brazilian Amazon.

early 1970s and now different successional forest stages and agroforestry account for most of the study area. In Bragantina, deforestation began about 100 years ago and now very limited primary forest can be found in this study area. Different successional forests and agroforestry dominate the study area. In the Ponta de Pedras, primary forest and savannah account for most of the study area and now some successional forests can be found in the disturbed areas. In the Machadinho d'Oeste, major deforestation began in the late 1980s. Primary forest still accounts for most of the study area, but initial and intermediate successional forests, agroforestry, and pasture dominate the deforested areas. The selected four study areas have different soil conditions, land use histories, landscape complexities, vegetation stand structures, and human activities, representing typical study areas in the Amazon. Hence, they are ideal for the exploration of how different biophysical environments influence the development of biomass estimation based on Landsat TM data.

The Altamira study area is located along the TransAmazon Highway in the Brazilian state of Pará with a combination of flat and rugged terrain. The city of Altamira and the Xingu River anchor the eastern edge of the study area. In the 1950s, an effort was made to attract colonists from north-east Brazil, who came and settled along streams as far as 20 km from the city centre. With the construction of the TransAmazon Highway in the 1970s, the population and older Caboclo settlers from earlier rubber eras claimed land along the new highway and legalized their land claims (Moran 1981). Early settlement was driven by geopolitical goals and political economic policies whose aim was to transfer production of staples like rice, corn and beans from the most southern Brazilian states to more northerly regions. Extensive deforestation has occurred since the 1970s. Various stages of successional forests are distributed along the TransAmazon Highway and feeder roads. Most successional forests are between 8 to 17 years old, some are greater than 20 years old. Nutrient-rich alfisols dominate in this study area, but some nutrient-poor ultisols and oxisols also exist. The annual rainfall is proximately 2000 mm, with the rainy season ranging from October to June the following year. Average annual temperature is 26°C.

The Bragantina study area is also located within the state of Pará and it has a flat topography interspersed by river channels that seasonally flood. The vegetation in this region is mostly composed of pasture and cropland, secondary growth forest, flooded forest, and a few remaining areas of dense mature forest. At the beginning of the twentieth century, almost one million hectares of dense tropical rainforest covered the Bragantina region; however, less than 2% of these forests remained by 1960. The dense forest that once surrounded the town of Castanhal had an average height of 23 m. Heavy occupation of this region has eliminated almost all dense forests and transformed the landscape into a mosaic comprised of a variety of succession vegetations (Tucker *et al.* 1998). Most successional forests are between 10 to 25 years old, and some are more than 50 years old. The nutrient-poor soils such as oxisols and ultisols and associate long-term land use history make the vegetation growth very slow. The annual rainfall is around 2200–2800 mm, with the rainy season ranging from December to August. Average annual temperature is 25–26°C.

The Ponta de Pedras study area is located in the estuarine region of the Amazon on Marajo Island. It is a topographically flat transitional region between two macro-environments with dense floodplain forests to the west and the more prominent natural savannah grasslands to the east. The forest presents uniform stratification consisting of large trees with an emergent canopy reaching 35 m and a sparse herbaceous layer. Disturbed areas, whether floodplain or upland forest, quickly become secondary forests with diverse stages of regrowth. Savannahs mainly consist of trees 2–5 m in height that are widely spread across a mantle of grasses such as *Aristida* and *Eragrostis*. Most successional vegetations are less than 15 years old. Upland nutrient-poor oxisols and floodplain alluvial soils dominate. The annual rainfall is proximately 3000 mm, with the rainy season ranging from December to early May. Average annual temperature is 27°C.

Rondônia has experienced high deforestation rates during the past two decades (INPE 2002) because of the national strategy of regional occupation and development initiated by the Brazilian government in the 1970s. The study area is located at Machadinho d'Oeste in north-eastern Rondônia. Deforestation rapidly increased in the 1990s and converted the mature forest landscape into coffee plantation, agroforestry, pasture, and successional forests. Most successional vegetations are less than 10 years old. The terrain is undulated, ranging from 100 to 400 m above sea level. Several soil types, including alfisols, oxisols, ultisols, and alluvial soils have been identified (Bognola and Soares 1999). The climate is classified as equatorial hot and humid, with tropical transition. The well-defined dry season lasts from June to August and the annual average precipitation is 2016 mm and the annual average temperature is 25.5°C (Rondônia 1998).

3. Methods

3.1 *Field data collection*

Field survey for the sample plots was conducted during the dry seasons of 1992 and 1995 in the eastern Amazon and in August 1999 in the western Amazon. A similar sampling strategy was used in eastern and western Amazon. The only difference is the size of sample plots. In eastern Amazon, 10 plots (10 m × 15 m) in each site are allocated and one randomly selected subplot (5 m × 2 m) is nested within each plot (Lu *et al.* 2004). Plots are designed to inventory trees and subplots are used to inventory saplings, seedlings, and herbaceous species. In the western Amazon, three nested plots and associated subplots with reduced size (10 m × 10 m and 3 m × 3 m) in each site are used to measure trees and saplings respectively (Lu and Batistella (in press)). The ground-cover estimation and individual counting were carried out for seedlings and herbaceous vegetation in the three nested 1 m × 1 m subplots. Lu *et al.* (2004) provided a detailed description of field data collection and biomass calculation based on vegetation inventory data at the site level in the eastern Amazon and Lu and Batistella (in press) in the western Amazon. Table 1 summarizes the datasets used in this research.

3.2 *Evaluation of complexity of forest stand structure*

Different parameters, such as tree height, diameter at breast height (DBH), and crown size, may be used to describe the characteristics of forest stand structure. In particular, the distribution of tree height is a good way to illustrate the vertical structure of a forest stand. In this research, entropy (*ENT*) was used to evaluate the

Table 1. Summary of datasets used in research.

Study area	No. of samples	AGB range($kg\,m^{-2}$)	Date for field data collection	TM image acquisition date
Altamira*§	20*	0.828 – 51.675	1992 and 1993	20 July 1991
Bragantina§	18	1.697 – 30.825	1994 and 1995	21 June 1994
Ponta de Pedras§	14	2.408 – 39.467	1992 and 1993	22 July 1991
Machadinho (SF)	26	2.397 – 15.987	1999	18 June 1998
Machadinho (MF)	14	11.132 – 49.470		

Note: * Four sites had coordinate errors. Only 16 sites were used in this research.
§ Soil samples were collected at the centre of vegetation inventory sample site in the Altamira, Bragantina, and Ponta de Pedras. No soil samples were collected in Machadinho study area.
SF: successional forests, MF: mature forest.

complexity of a stand structure based on the probability of tree height distribution in a sample. It can be expressed as

$$ENT = -\sum_{i=j}^{h} P_i \log_2(P_i) \quad \text{and} \quad P_i = n_i \Big/ \sum_{i=j}^{h} n_i \tag{1}$$

where P_i is the probability for ith tree height, n_i is the number of trees in the ith tree height, j is the minimum tree height, and h is the maximum tree height. For successional forest samples, j is equal to or greater than 5 m because the majority of trees have heights greater than 5 m. For mature forest, j is equal to or greater than 10 m because the majority of trees have heights greater than 10 m. In general, more complexity of the forest stand structure yields higher *ENT* values.

In eastern Amazon, the scatterplot consisting of entropy and AGB (or age) of successional forests is used to compare the forest stand characteristics between Altamira and Bragantina, to explore how different study areas with various stand structures influence AGB estimation performance. Both study areas belong to the extremes in the complexity of forest stand structure and soil conditions. Ponta de Pedras is not included in this analysis because it belongs to the middle of Altamira and Bragantina in biophysical conditions and because the number of samples for successional forests is limited. In western Amazon, the scatterplot consisting of entropy and AGB is used to compare the forest stand structures between successional and mature forests, to explore the impacts of different complexity of forest stand structures on AGB estimation.

3.3 *TM image preprocessing*

Accurate geometric rectification and atmospheric calibration are two important aspects in image preprocessing. In this research, the TM images (see table 1 for image acquisition dates) were geometrically rectified into a Universal Transverse Mercator (UTM) projection using control points taken from topographic maps of 1 : 100 000 scale. A nearest-neighbour resampling technique was used and an rms. error of less than 0.5 pixels was obtained for each TM image during the image rectification. An improved image-based dark object subtraction (DOS) model was used for atmospheric correction (Lu *et al.* 2002). During radiometric calibration using the DOS model, gain and offset for each band and Sun elevation angle were obtained from the image header file. The path radiance was identified based on clear water for each band. The atmospheric transmittance values for visible and near-infrared bands were derived from radiative transfer code (Chavez 1996). For middle infrared bands, the atmospheric transmittance was set to 1. The surface reflectance values fall within the range of 0–1. For convenience of data analysis, the reflectance values were rescaled to the range of 0–100 by multiplying 100 for each pixel.

3.4 *TM image processing*

Lu *et al.* (2004) examined the relationships between TM spectral responces (i.e. TM spectral bands, vegetation indices, linear transforms) and AGB in the three study areas in the eastern Amazon and found that a single band TM5 and linear transformed indices, such as the first component from the principal component analysis and the brightness from the tasselled cap transform, are most strongly correlated with AGB, somewhat independent of biophysical environments. This conclusion is in broad agreement with other research (Roy and Ravan 1996, Steininger 2000, Foody *et al*. 2001, Zheng *et al*. 2004). On the other hand, Lu *et al*. (2004) found that different biophysical environments can significantly influence the correlations between AGB and TM spectral responses. In another study, Lu and Batistella (in press) examined the relationships between the GLCM based textures and AGB in the western Amazon based on successional and mature forests, respectively. It was found that most textures are weakly correlated with successional forest biomass, but some textures such as *Contrast* texture measured with TM band 5 and 19×19 window size are significantly correlated with mature forest biomass. Conversely, TM spectral signatures are significantly correlated with successional forest biomass, but weakly correlated with mature forest biomass. Based on the previous work on the examination of the relationships between AGB and TM spectral signatures in eastern Amazon and the relationships between AGB and GLCM based textures in western Amazon, this research aims to explore the incorporation of textures and spectral responses for improvement of AGB estimation performance based on different biophysical environments in the Brazilian Amazon.

After TM image preprocessing, four types of texture measures—mean Euclidean distance (MED), variance, skewness, and kurtosis—with different window sizes (3×3, 5×5, 7×7, 9×9, and 15×15) for each TM band were tested in the three study areas in the eastern Amazon (Lu 2001). In the western Amazon, eight GLCM based texture measures (i.e. mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation) associated with five TM bands (bands TM2, 3, 4, 5, and 7), and seven different sizes of moving windows (i.e. 5×5, 7×7, 9×9, 11×11, 15×15, 19×19, and 25×25) were tested (Lu and Batistella (in press)). A detailed description of the texture measures used in this paper can be found in Lu (2001) and Lu and Batistella (in press), and TM spectral responses in Lu *et al*. (2004).

3.5 *Development of aboveground biomass estimation models*

In AGB estimation research, multiple regression analysis is the most often used approach (Roy and Ravan 1996, Steininger 2000, Zheng *et al*. 2004), thus, it is also used in this study. Different combinations of spectral responses and textures are explored based on various biophysical conditions. In this research, all the sample data had accurate coordinates that were provided by Global Positioning System (GPS) devices and geometrically rectified TM colour composites during the fieldwork. These sample data were linked to image variables to extract the mean value for each sample. A window size of 3×3 pixels was used to create an area of interest (AOI) for each sample. Retrieval of mean value for each sample was conducted based on an overlay of the AOI layer on corresponding TM spectral image, vegetation indices, or textures. After the image values for these samples were extracted, Pearson's correlation coefficient was used to analyse relationships between AGB and remote sensing derived variables, including TM spectral signatures, vegetation indices, and textures. The AGB was used as a dependent variable, the derived remote sensing variables were used as independent variables, and a stepwise regression analysis was used to develop AGB estimation models. The coefficient of determination (R^2) is used to evaluate a regression model performance because it measures the percentage of variation explained by the regression model. Although validation of the estimated results is an important part in the AGB estimation procedure, the difficulty in collecting sufficient ground reference data makes validation impossible in this research. However, qualitative analysis is conducted based on visual comparison of the estimated results and corresponding TM colour composite.

4. Results and discussion

4.1 *Analysis of forest stand structure*

Figure 2 provides a comparison of successional forest stand structures between Altamira and Bragantina. The successional forest samples with similar age or biomass density between the two study areas demonstrate significantly different entropy values, i.e. the entropy in Altamira is much higher than in Bragantina, implying that the forest stand structure in Altamira is much more complex than that in Bragantina. This indicates that Altamira is likely to present more canopy shadowing. As previous work indicates, the AGB and TM spectral signature correlation in Altamira is much weaker compared with that in Bragantina, but converse for the AGB and texture correlation (Lu 2001, Lu *et al.* 2004). A marked shadow problem in Altamira is an important factor in reducing the relationships between AGB and remote sensing spectral responses. Conversely, it enhances the relationships between AGB and textures. Bragantina has less shadow, resulting in a high correlation between AGB and spectral responses, but has a lower correlation between AGB and textures.

Vegetation stand structure and associated canopy shadows, canopy closure, and species composition were regarded as important factors affecting the vegetation

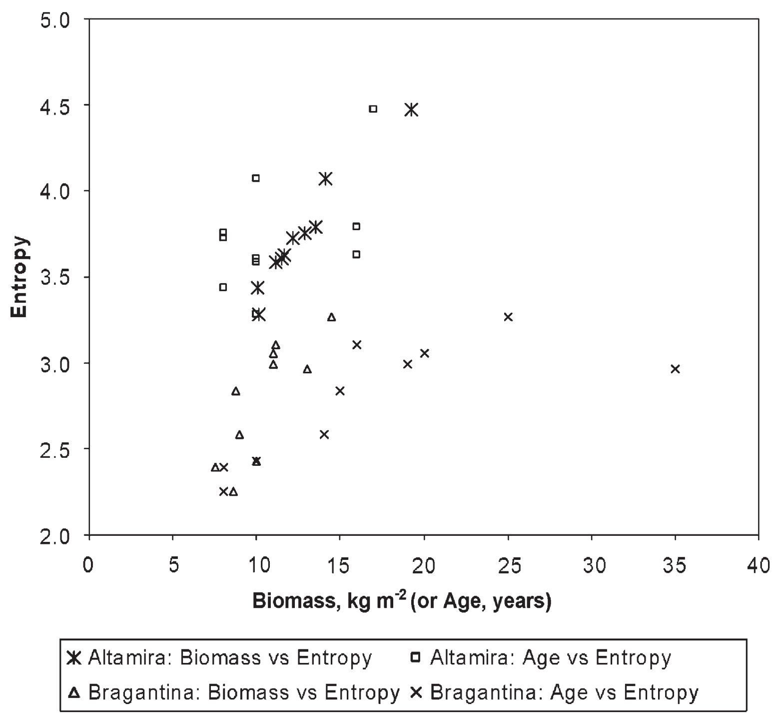

Figure 2. Comparison of aboveground biomass (age)—entropy relationships in Altamira and Bragantina, eastern Brazilian Amazon.

reflectance captured by optical sensors (Steininger 2000). Figure 3 graphically illustrates the relationships between entropy and AGB for successional and mature forests. For successional forests, the canopy structure becomes more complicated as AGB increases, up to a certain amount of AGB (such as $15\,kg\,m^{-2}$). For mature forest, although AGB varies greatly from approximately $11\,kg\,m^{-2}$ to $50\,kg\,m^{-2}$, the entropy increase is not obvious, especially when the AGB reaches proximately $17\,kg\,m^{-2}$. Usually, mature forests in different sites have highly variable AGB amounts depending on the soil condition, topography, and degradation by selective logging or fire. However, the complicated vegetation stand structures in mature forest and in advanced successional forests often result in similar TM reflectance even if AGB varies significantly. This situation is often called data saturation. Similar cases are also found in other study areas, such as in Manaus of the Brazilian Amazon, where canopy reflectance of the successional forests saturated when biomass density increased to about $15\,kg\,m^{-2}$ or vegetation ages reached over 15 years (Steininger 2000).

As vegetation grows from initial, to intermediate, and until advanced succession, the stand structure gradually becomes complex, up to a certain degree, such as shown in figure 3, when the entropy value reaches proximately 3.5. Thus, the successional forest biomass is significantly correlated with TM spectral signatures. Conversely, the similar forest stand structures among the mature forest samples result in data saturation, generating poor correlation between mature forest biomass and TM spectral signatures. Because textures can reduce the impacts of forest stand structure and associated canopy shadow problem, the correlation between texture and AGB becomes significant. Understanding the role of forest stand structure and its impacts in AGB and TM reflectance relationships is important and helpful for selecting suitable spectral signatures or textures for development of AGB estimation models.

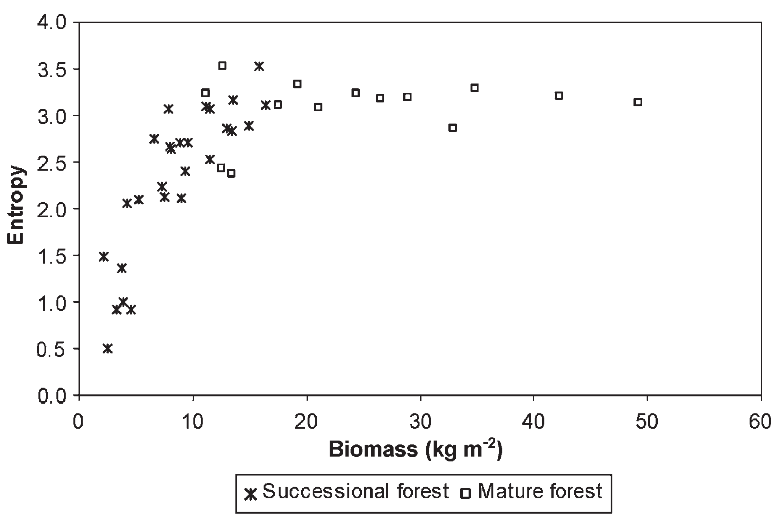

Figure 3. Comparison of aboveground biomass—entropy relationships in successional and mature forests in Machadinho, western Brazilian Amazon.

4.2 *Biomass estimation*

Linear regression analysis was used to develop AGB estimation models based on the integration of vegetation inventory data and remote sensing variables. Table 2 provides the best regression models identified according to spectral responses, textures, and a combination of spectral responses and textures, respectively. Comparing the spectral responses used in the eastern Amazon, the AGB estimation has best performance in Bragantina with relatively simple stand structure, and poorest in Altamira with complicated forest stand structure. Conversely, comparing the textures used in this study, the AGB estimation has best performance in Altamira and poorest in Bragantina. Considering the AGB estimation performance between successional and mature forests in the western Amazon, the spectral signature provides better AGB estimation performance for successional forest than for mature forest, but the converse for the textures. A combination of spectral and textural features improves the AGB estimation performance. The role of textures in improving the AGB estimation performance is more important in Altamira than in Bragantina, also texture is critical for mature forest biomass estimation, but relatively less important for successional forest biomass estimation.

The beta value in table 2 provided a means of measuring the relative changes in variables on a standard scale. It indicated how much change in the dependent variable was produced by a standardized change in one of the independent variables when the others were controlled. The beta values confirmed that texture was more important in Altamira than in Bragantina. It was also valuable in improving model performance in Ponta de Pedras. Table 2 implies that Landsat TM image is more successful for AGB estimation in successional forests than in mature forests. In western Amazon, the majority of successional forests have less than 12 years old at the time of image acquisition and their biomass density is less than 12 kg m^{-2}, while the majority of mature forest has biomass density of greater than 20 kg m^{-2}. The large differences in biomass density and associated forest stand structure between successional and mature forests make significant different performance in AGB estimation. This research implies that neither spectral signatures, nor textures, nor combination of spectral signature and texture can provide satisfactory AGB estimation for mature forest.

Figure 4 provides an example of AGB estimation result in the Altamira study area. Although no validation or accuracy assessment of the AGB estimation result is conducted, visually checking the spatial distribution of the AGB estimation result indicated that it is reasonable and satisfactory. For example, visually comparing the estimated biomass image with TM 4-5-3 colour composite indicates that the biomass distribution coincides with the distribution of vegetation growth stages, i.e. the higher biomass density corresponds to the higher vegetation growth stages. In Altamira, those areas where AGB is larger than 20 kg m^{-2} are mainly mature forest, distributed away from the TransAmazon Highway. Those areas where AGB ranges from 15 to 20 kg m^{-2} are mainly degraded mature forest or advanced successional forests. Most of them are distributed near the mature forest. Those areas where AGB is less than 15 kg m^{-2} are different successional forests, scattered in the agricultural areas. This result implies that the AGB models developed from a small sample site can be successfully extrapolated to a larger study area with similar biophysical environments.

Table 2. Summary of aboveground biomass estimation models using Landsat TM derived variables.

Variables	Study areas	Models	R^2	Beta Value
Spectral responses	Altamira	$-49.892-202.045$ ND54	0.404	
	Pedras*	$95.196-5.852$ TM5	0.683	
	Bragantina	$68.116-1.832$ TM4	0.701	
	Machadinho (SF)	$66.772-1.392$ TM4	0.746	
	Machadinho (MF)	$102.414-5.496$ TM5	0.158	
Textures	Altamira	$89.461-151.495$ VARtm2_9	0.708	
	Pedras*	$35.109-6.455$ KUtm3_5	0.493	
	Bragantina	$21.038-3.766$ VARtm5_15	0.304	
	Machadinho (SF)	$16.462-0.227$ VARtm4_15	0.232	
	Machadinho (MF)	$13.457+1.929$ CONtm5_19	0.392	
Combination of spectral and texture	Altamira	$122.288-1.078$ KT1 -128.913 VARtm2_9	0.772	-0.28 (sp), -0.72 (txt)
	Pedras*	$65.239-10.189$ TM7 -3.816KUtm3_5	0.748	-0.58 (sp), -0.42 (txt)
	Bragantina	$64.037-1.651$ TM4 $+1.405$ SKtm4_9	0.780	-0.76 (sp), 0.29 (txt)
	Machadinho (SF)	$48.082-0.806$ TM4 -0.098 VARtm4_15	0.755	-0.71(SP), -0.24(txt)
	Machadinho (MF)	$75.331-4.321$ TM5 $+1.789$ CONtm5_19	0.498	-0.31(sp), 0.65(txt)

Note: * Ponta de Pedras; SF and MF: successional forest and mature forest; sp and text: the variables of spectral signatures and textures; TM4, TM5, and TM7: Landsat TM bands 4, 5, and 7; ND54 is the ratio (TM5 − TM4)/(TM5 + TM4); KT1: the first component from the tasselled cap transform based on Landsat TM images; VARtma_b: variance texture measure with TM band a and associated $b \times b$ window size; KU, SK, and CON: Kurtosis, skewness, and contrast texture measures.

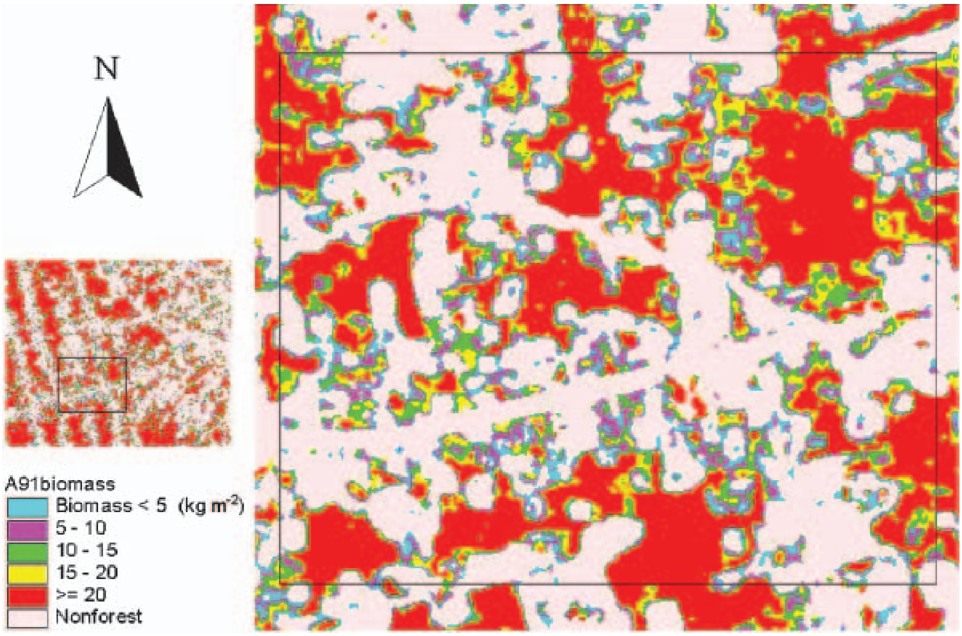

Figure 4. Biomsss estimation result for part of the study area in Altamira.

4.3 *Discussion*

Model transferability is a major concern after models are developed but, in reality, it is often difficult to transfer one model developed in a specific study area to other study areas because of the limitation of the model itself and the nature of remotely sensed data. Foody *et al.* (2003) discussed the problems encountered in model transfer. Many factors, such as uncertainties in the remotely sensed data (image preprocessing and different stages of processing), AGB calculation based on field measurements, the disparity between remote sensing acquisition date and field data collection date, and the size of sample plot compared with the spatial resolution of remotely sensed data, could affect the success of model transferability. Each model has its limitation and optimal scale for implementation. When using a regression model, attention should be given to understanding the applicable scale implemented in the original models. Models developed in one study area may be transferred to (1) across-scene data, which have similar environmental conditions and landscape complexity, to estimate AGB in a large area; and (2) multi-temporal data of the same study area for AGB dynamical analysis if the atmospheric calibration is accurately implemented. The spectral signatures, vegetation indices, and textures are often dependent on the image scale and environmental conditions. Caution must be taken to ensure that there is consistency between the images used in scale, atmospheric and environmental conditions. Calibration and validation of the estimated results may be necessary using reference data when using transferred models.

The data sources used for AGB estimation may include field-measured sample data, remotely sensed data, and ancillary data. A high-quality sample dataset is a prerequisite for developing AGB estimation models as well as for validation or assessment of the estimated results. Direct measurement of AGB in the field is very difficult. In general, AGB is calculated using allometric equations based on measured DBH and/or height, or from the conversion of forest stocking volume. These methods generate many uncertainties and calibration or validation of the calculated AGB is necessary. Previous research has discussed the uncertainties of using allometric equations (Brown *et al.* 1995, Keller *et al.* 2001, Ketterings *et al.* 2001) and of conversion from stocking volume (Fearnside 1992). A detailed discussion about the collection of AGB samples and its quality is beyond the scope of this paper. Also it is important to ensure that the remote sensing data, ancillary data, and sample plots are accurately registered when ancillary data are used for AGB estimation. Understanding and identifying the sources of uncertainties and then devoting efforts to improving them are keys to a successful AGB estimation. More research is needed in the future for reducing the uncertainties from different sources in the AGB estimation procedure.

Many remote sensing variables, including spectral signatures, vegetation indices, transformed images, and textures, may become potential variables for AGB estimation. However, not all variables are required because some are weakly related to AGB or they have high correlation with each other. Hence, selection of the most suitable variables is a critical step for developing an AGB estimation model. In general, vegetation indices can partially reduce the impacts on reflectance caused by environmental conditions and shadows, thus improving correlation between AGB and vegetation indices, especially in those sites with complex vegetation stand structures (Lu *et al.* 2004). On the other hand, texture is an important variable for improving AGB estimation performance. One critical step is to identify suitable textures that are strongly related to AGB but are weakly related to each other. However, selection of suitable textures for AGB estimation is still a challenging task because textures vary with the characteristics of the landscape under investigation and images used. Identifying suitable textures involves the determination of appropriate texture measures, moving window sizes, image bands, and so on (Franklin *et al.* 1996, Chen *et al.* 2004). Not all texture measures can effectively extract biomass information. Even for the same texture measure, selecting an appropriate window size and image band is crucial. A small window size, such as 3×3, often exaggerates the difference within the moving windows, increasing the noise content on the texture image. On the other hand, too large a window size, such as 31×31 or larger, cannot effectively extract texture information due to smoothing the textural variation too much. Also, a large window size implies more processing time. In practice, it is still difficult to identify which texture measures, window sizes, and image bands are best suited to a specific research topic and there is a lack of guidelines on how to select an appropriate texture. More research is needed to develop suitable techniques for identification of the most suitable textures for biomass estimation.

Another advanced method for selection of suitable variables, that is likely to be important in the future, is to use neural network. Neural network analysis may provide a new insight for AGB estimation and is encouraged for AGB studies in the future. For example, a neural network may be used in different ways for extracting vegetation variables, such as inverting physically based models when lacking effective numerical optimization techniques to invert models, used as a variable selection tool to determine suitable variables, and used as adaptable systems to incorporate different kinds of data such as spectral data and ancillary data for extraction of vegetation variables (Kimes *et al.* 1998). In addition to remotely sensed data, different soil conditions, terrain factors, and climatic conditions may influence AGB estimation because they affect AGB accumulation rates and development of forest stand structures. Incorporation of these ancillary data and remote sensing data may improve AGB estimation performance. Geographical Information System (GIS) techniques can be useful in developing advanced models through the combination of remote sensing and ancillary data.

5. Conclusion

This study demonstrates that Landsat TM image is more successful for AGB estimation in successional forests than in mature forests. Textures play an important role in improving AGB estimation performance, especially for those sites with complicated forest stand structure. A combination of spectral responses and textures improves AGB estimation performance comparing pure spectral responses or textures. The complexity of forest stand structure is the main factor making the AGB estimation difficult. Different biophysical conditions significantly influence AGB estimation performance, resulting in difficulty in transferring the developed AGB models to different study areas.

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