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Change Detection of Successional and Mature Forests Based on Forest Stand Characteristics Using Multitemporal TM Data in Altamira, Brazil

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CHANGE DETECTION OF SUCCESSIONAL AND MATURE FORESTS BASED ON FOREST STAND CHARACTERISTICS USING MULTITEMPORAL TM DATA IN ALTAMIRA, BRAZIL

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ABSTRACT

Previous research has shown that vegetation change detection is very difficult in a moist tropical region using remote sensing spectral data due to complex stand structure, abundant vegetation species, and complex landscape environment. Although biomass change information is valuable for many applications such as carbon emission, most research involving vegetation change detection has provided only area change statistics and spatial distribution. In this paper, forest stand parameters, i.e., ratio of tree biomass to total above-ground biomass (RTB) and above-ground biomass (AGB) were developed in the Altamira region of Brazil. The RTB approach was used to distinguish successional and mature forests. The RTB images and AGB images from multiple dates, which were developed through integration of vegetation inventory and remote sensing data, respectively, were used to detect successional and mature forest change and biomass change. This research concluded that the RTB and AGB models developed for one date of TM images can be applied to TM images from other dates in the same study area. They were found appropriate to use for vegetation change detection associated with biomass change in the Amazon basin. However, calibration of reflectance differences caused by different environmental conditions, such as moisture, is critical for successfully implementing change detection. Key words: change detection, tropical forest, Amazon, forest stand parameter.

INTRODUCTION

The Brazilian Amazon contains the largest continuous rain forest in the world. It has a special place in issues concerning global warming, because its vast areas of tropical forest represent a potentially large source of carbon/greenhouse gas emissions (Fearnside, 1998). Destruction of Amazonian forests is responsible for 7% of the total carbon dioxide (CO_2) emissions provoked by fossil fuel emission (Moran et al., *Integrating* 1994). The deforestation rates in the Amazon basin rose sharply during the 1970s and 1980s and more recently during the mid-1990s because of road-building, logging, agropastoral expansion associated with national political and economic policies (Moran et al., *Integrating* 1994; Skole et al., 1994). The estimated deforestation rate between 1978 and 1988 was 15,000–20,000 km^2 per year (Skole et al., 1994) and approximately 17,000 km^2 per year between 1988 and 1996 (INPE, 1998). Deforestation typically leads to tremendous effects on climate change (Shukla et al., 1990; Houghton, 1991), biological diversity (Skole and Tucker, 1993), the hydrologic cycle, and soil erosion and degradation. Therefore, information about deforestation and regrowth detection is valuable for better managing tropical forest resources and predicting potential environmental change. Remote sensing technology has the potential to monitor deforestation and regrowth rates with high temporal and spatial resolutions and has been used for land-use and land-cover classification and change detection (Moran, 1993; Brondizio et al., 1994, 1996; Moran and Brondizio, 1998), deforestation (Conway et al., 1996; Brondizio et al., in press), restoration (Moran et al., 1996), and secondary succession (SS) classification (Lucas et al., 1993; Mausel et al., 1993; Li et al., 1994; Moran et al., *Integration* 1994, *Secondary* 1994).

Research on deforestation of Amazon moist tropical forests is increasingly attracting international attention. However, scientists have obtained different results and have reached different conclusions about important Amazon succession processes depending on the study areas and methods used. Many important scientific questions remain unanswered about deforestation and afforestation in the Amazon basin. There is not a clear understanding about deforestation rates, regeneration rates, spatial distribution of SS stages and mature forest, and biomass change associated with succession. An efficient method used for classification of moist tropical forests and SS stages is still lacking. Effective classification and vegetation change detection in the Amazon basin using remote sensing spectral data are difficult due to the complex stand structures, abundant species, and complex landscapes (Mausel et al., 1993; Brondizio et al., 1994; Moran et al., *Secondary* 1994; Lu, 2001).

Definition of the various SS stages and mature forest is still disputed. In field surveys, vegetation age is the easiest way to identify the different SS stages. However, the same regrowth stage in different locations can have greatly different forest stand structures and tree species compositions due to differences in soil fertility, human activity, and land-use history (Moran et al., *Effects* 2000, *Strategies* 2000, in press). Tucker et al. (1998) identified initial, intermediate, and advanced succession forests (here referred to as SS1, SS2, and SS3) using six factors (tree basal area, average total height, mode total height, average diameter, total height standard deviation, and percent tree contribution to total basal area) in eastern Amazonian regions (Altamira and Bragantina, Brazil), excluding mature forest. Moran and Brondizio (1998) distinguished the SS stages based on average stand height and basal area. However, overlap remains between SS2 and SS3 and between SS3 and mature forest. Lu (2001) found that ratio of tree biomass to total biomass (RTB) was a good forest stand parameter that distinguished different SS stages and mature forest based on the canonical discriminant analysis in the eastern Amazon. The RTB responds to different forest stand structures because tree biomass has a different proportion to the total AGB during different regrowth stages.

The above methods are limited to the use of field survey data and are limited in extrapolating to large areas in the moist tropical regions. Remote sensing has the advantage in that it can cover and acquire a large data set from a large area in digital format. Mausel et al. (1993) employed the ECHO (extraction and classification of homogeneous objects) classifier to classify TM data into different SS stages in Altamira. Similar studies were conducted in other areas, such as in Pedras, by Moran et al. (1994), Li et al. (*Secondary* 1994), and Brondizio et al. (1996). However, all these studies were conducted in small areas with associated detailed ground-truth data. It is not appropriate to directly extrapolate to a large area or other study areas without abundant ground-truth data because of effects caused by different environmental conditions such as variation in soil types and moisture, different human activities, and land-use history. Classification accuracy depends on the landscape complexity of a study area, the availability and quality of ground-truth data, and training data that are truly representative of features of interest. A crucial step in using remotely sensed data for classification of different SS stages and mature forest is selection of appropriate training samples. This is often difficult and time consuming. Often SS stages are not clearly distinct; for example, old SS2 and young SS3 forests appear very similar. The RTB value is a good stand parameter to identify different SS stages based on the field vegetation inventory data. It can be developed from remotely sensed data through multiple regression models (Lu, 2001). The advantages of the RTB thresholding method include minimizing the influences of ground truth variation and promoting the flexibility of reclassification by adjusting RTB thresholding ranges based on the characteristics of the study areas. Potentially, the RTB model developed on one date of TM images can be transferred to another date of TM images in the same study area to produce vegetation change detection if reflectance differences caused by variation in environmental conditions are considered.

Many change detection techniques have been developed and reviewed (Singh, 1989; Mouat et al., 1993; Deer, 1995; Coppin and Bauer, 1996; Jensen, 1996; Lu, 2001), such as post-classification comparison, spectral/temporal classification, image differencing, image regression, image ratioing, vegetation index differencing, principal component analysis, and change vector analysis. Research results found in the literature mainly focused on spatial distributions of land-cover change or vegetation change. Rarely has research focused on quantitative change detection of AGB, despite the importance of data for forest management, carbon emission estimation, wildlife protection, soil and water protection, and environmental monitoring. Ideally, a complete change detection of forest cover types should provide the following information: (1) area change and change rate, (2) biomass (or other forest stand parameters) change and change rate, (3) spatial distribution of change types, (4) change direction of forest cover types, and (5) accuracy of change detection. Previous research mainly involved area change and spatial distribution of cover change based on remote sensing spectral data, but ignored biomass change (or other forest stand parameters) due to the difficulty in establishing an appropriate biomass estimation model using remotely sensed data and the difficulty in field data collection. This paper contributes to a better understanding of vegetation change detection and biomass change processes associated with integration of field vegetation inventory data and Landsat TM images.

STUDY AREA AND DATA SETS

The Altamira study area is located along the Transamazon Highway in the Brazilian state of Para (Figure 1). The city of Altamira and the Xingu River anchor the eastern edge of the study area. In the 1950s colonists were attracted from northeast Brazil and settled along streams as far as 20 km from the city center. With the construction of the Transamazon Highway in 1970, this population and older Caboclo settlers from the earlier rubber economic era claimed land along the new highway through the help of government-sponsored programs. Early settlement was driven by geopolitical goals and political economic policies that focused on occupying the region and establishing production areas of staples like rice, corn and beans. The region has had a gradual shift to a more diverse set of land uses: pasture, cocoa, sugar cane, black pepper, and staple crops. Mahogany is beginning to be planted in cocoa groves as a diversification strategy and can be expected to benefit landowners who have the best soils in the area (Moran et al. in press). The dominant native types of vegetation are mature moist forest and liana forest. Nutrient-rich alfisols, as well as nutrient-poor ultisols and oxisols are found in the Altamira study area. This area has experienced high rates of deforestation and regrowth associated with implementation of agropastoral projects. Annual rainfall in Altamira is approximately 2,000 mm and is concentrated from late October through early June, and average temperature is 26°C.

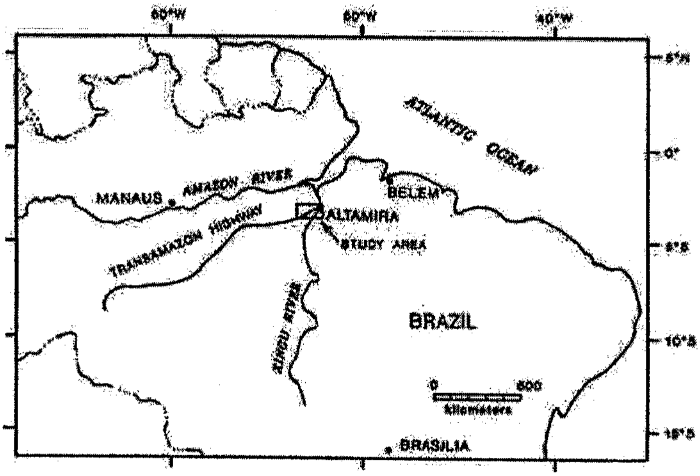


Figure 1. Study Area

Field vegetation inventory data, soil data, and land-use history information were collected during the dry seasons of 1992 and 1993. Details about the field data collection method and RTB calculation used are provided in Lu (2001). The RTB calculation based on field inventory data is described below.

Equation [1] (Nelson et al., 1999) was used to calculate biomass for those trees and saplings with a diameter at breast height (DBH) of less than 25 cm, and equation [2] (Overman et al., 1994) was used to calculate biomass for those trees with a DBH of greater than or equal to 25 cm. AGB (kg/m^2) and RTB were calculated using formulas [3] and [4] at the site data-collection level.

$$\ln(DW1) = -2.5202 + 2.1400 \cdot \ln(D) + 0.4644 \cdot \ln(H) \,, \qquad [1]$$

$$\ln(DW2) = -3.843 + 1.035 \cdot \ln(D^2 * H) \,, \qquad [2]$$

$$AGB = \left(\sum_{i=1}^{m} DW1_i + \sum_{j=1}^{n} DW2_j\right)/AP + \left(\sum_{k=1}^{s} DW1_k\right)/AS \,, \qquad [3]$$

$$RTB = \text{tree biomass} / \text{total biomass} \,, \qquad [4]$$

where D is the DBH (cm) and H is the total tree height (m). DW1 is individual tree or sapling biomass (in kg) when DBH is less than 25cm, DW2 is the individual tree biomass when DBH is greater than or equal to 25 cm, m is the total tree number when DBH falls within 10–25 cm in a plot, n is the total tree number when DBH is greater than or equal to 25 cm in a plot, and s is the total sapling number when DBH falls within 2–10 cm in a subplot area. AP and AS are the plot area and subplot area (m^2), respectively.

METHODS

Figure 2 illustrates the framework of vegetation change detection associated with biomass change detection. The multitemporal TM images were geometrically rectified and registered into UTM projection. All TM images were atmospherically corrected using an improved image-based DOS (dark object subtraction) model (Chavez, 1996; Lu et al., in press). The atmospheric correction model eliminated or reduced the effects caused by sun zenith angle, solar radiance, atmospheric scattering and absorption, but it cannot eliminate the reflectance difference caused by different environmental conditions such as soil moisture among the multitemporal TM images. In order to successfully transfer the RTB or AGB models developed in TM image at a given date to another TM image with a different date in the same study area, it is necessary to normalize or calibrate the reflectance differences caused by different environmental conditions among multitemporal TM images.

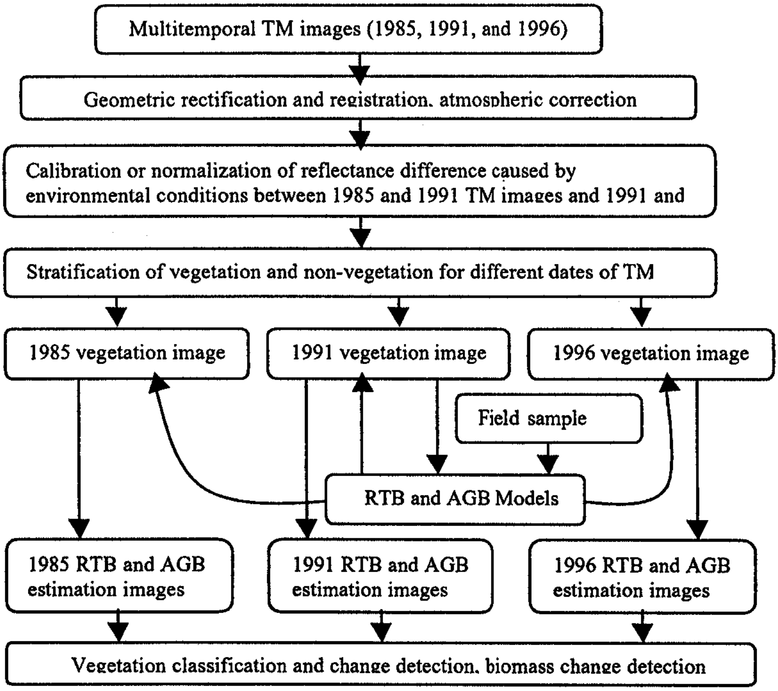


Figure 2. Framework for Classification and Change Detection

In practice, the reflectance values of the same land-cover type vary on different dates of TM images due to the effects of different environmental conditions. Linear regression models were developed for each TM band by selecting the sample data from multitemporal TM images. In this research, one date of TM image (1991) was selected as the reference image, and other dates of TM images (1985 and 1996) as the predicted image. Regression equations were developed by correlating the values of normalization targets in both the image being normalized and the reference image, based on the assumption that after atmospheric correction the values of the normalization targets are constant and changes of these values in other images are caused by environmental conditions (Lu, 2001).

In order to reduce confusion between vegetation and non-vegetation (bare soil, water, road, residence, crops, and pastures), it is necessary to mask out the non-vegetation areas, so only vegetation areas are kept for classification and change detection. An unsupervised ISODATA classifier was used to distinguish vegetation from non-vegetation areas before developing the RTB and AGB models. The following RTB and AGB estimation models were developed through integration of vegetation inventory data and TM image data that were identified from vegetation indices and texture measures by stepwise regression analysis (Lu, 2001).

$$RTB = 1.617+0.229*KT3-0.94*VARtm2\_7 , \qquad [5]$$

$$AGB\ (kg/m^2) = 122.288-1.078*KT1-128.913*VARtm2\_9 , \qquad [6]$$

where KT1 and KT3 are the brightness and wetness components, respectively, of the Tasseled Cap transform; and VARtm2_7 and VARtm2_9 are the variance textures with band TM 2 and 7x7 and 9x9 window sizes, respectively.

Different succession stages have smooth transitions from one stage to the next, making distinction difficult between them using remote sensing spectral data. However, the RTB value corresponds to SS stages and mature forest (Lu, 2001). It changes from 0% to 100% when vegetation grows from young succession to advanced SS stages and ultimately mature forest. Table 1 gives the definition and characteristics of different SS stages used in this research. Biomass statistics for each SS stage and mature forest were also developed though a combination of estimated AGB images and RTB thresholding classified images.

Table 1. Characteristics of Different Vegetation Classes

RTB value	Definition	Characteristics
0–20%	SSa	Dominated by SS1 in which saplings and seedlings account for the majority of total vegetation biomass. Some young SS2 vegetations are also included.
20–40%	SSb	SS2
40–60%	SSc	Dominated by SS3, some old SS2 vegetations are also included.
60–80%	SSd	A mixture of old SS3 and some mature forest with small biomass amount.
80–100%	MF	Mature forest which trees account for the majority of total biomass

Visual interpretation of color composites with multitemporal RTB or AGB images provides qualitative information about vegetation change during the periods of change detection. Detailed quantitative vegetation change analyses were also developed through comparison of multitemporal RTB threshold classified images pixel by pixel. A biomass change image associated with a forest cover change image was also analyzed to produce detailed biomass change information for different vegetation change directions. Ten different change directions were grouped and defined as follows:

(1) Forest deforestation (For Def): mature forest in prior date converted to non-forest or SSa in post date.
(2) SS deforestation (SS Def): different SS stages in prior date converted to non-forest or SSa in post date.
(3) Forest degradation (For Deg): mature forest in prior date degraded to different SS stages in the post date.
(4) SS degradation (SS Deg): more mature SS stages in prior date degraded to less mature SS stage in the post date due to disturbance or fragmentation.
(5) SS growth (SS Grw): less mature SS stages in prior date transformed to more mature SS stages in the post date, such as from SS1 to SS3.
(6) SS transfer to forest (SS-For): advanced SS stages such as SSc and SSd in prior date transformed to similar mature forest state in post date.
(7) Non-forest to SS (Non-SS): non-forest areas such as pasture/crops in prior date changed to different SS stages in post date.
(8) SS unchanged (SS-unchg): remained the same SS stages in both dates.
(9) Mature forest unchanged (MF-unchg): mature forest stage existed on both dates.
(10) Non-forest: non-forest areas including bare soils and crops/pastures remained unchanged in both dates.

RESULTS AND DISCUSSION

The RTB and AGB models were developed though integration of Landsat TM images (1991) and a limited set of field vegetation inventory data, respectively. Table 2 provides area and biomass information for each vegetation class derived from 1991 TM images. Biomass for each vegetation class was derived through using statistics of the estimated AGB image and the RTB thresholding image. Mature forest has much higher biomass density (biomass amount per hectare) than any other vegetation stage.

Table 2. Summaries of Area and Biomass Characteristics Derived from 1991 TM Image

Class	Area (ha)	Biomass (ton)	Biomass density (ton/ha)
SSa	578.25	14478.66	25.04
SSb	3176.91	244108.44	76.84
SSc	9092.88	1416009.78	155.73
SSd	12870.27	3315566.43	257.61
Forest	14194.71	4856145.39	342.11

After reflectance normalization among multitemporal TM images, the RTB and AGB models developed using 1991 TM images were transferred to 1985 TM image and 1996 TM image, respectively, in the same study area. Table 3 summarizes area and biomass statistical results for each vegetation class and their change information. Between 1985 and 1991, mature forest clearing accounted for 4,452 ha with 1,999,198 t (t) of biomass loss. However, the SSc increased 3,012 ha associated with 524,928 t of biomass accumulation. Between 1991 and 1996, the area and biomass decreased for all vegetation classes. In particular, mature forest and SSc presented the highest decrease in area and biomass amount during this period. Mature forest lost 2,823 ha with 880,406 t of biomass loss, and SSc lost 1,695 ha with 476,715 t of biomass loss. Between 1985 and 1991, mature forest and degraded mature forest lost 899 ha per year, associated with 445,985 t of biomass loss per year. Different SS stages lost 185 ha per year, with 20,251 t of biomass loss. Between 1991 and 1996, the deforestation rate was 601 ha per year with biomass loss of 194,563 t per year because of the loss of mature forest and degraded mature forest. Different SS stages lost 477 ha per year with biomass loss of 116,700 t per year.

Table 3. Area and Biomass Change for Each Vegetation Growth Stage in the Altamira Area

Class	Area (ha) for each class			Area change (1985–1991)		Area change (1991–1996)	
	1985	1991	1996	Area change (ha)	Annual change (ha/yr)	Area change (ha)	Annual change (ha/yr)
SSa	1,052.01	578.25	377.19	-473.76	-78.96	-201.06	-40.21
SSb	3,812.85	3,176.91	2,686.77	-635.94	-105.99	-490.14	-98.03
SSc	6,080.76	9,092.88	7,397.64	3,012.12	502.02	-1,695.24	-339.05
SSd	13,811.76	12,870.27	12,684.51	-941.49	-156.92	-185.76	-37.15
Forest	18,646.74	14,194.71	11,372.04	-4,452.03	-742.01	-2,822.67	-564.53
Non-forest	24,397.20	27,888.30	33,283.17	3,491.10	581.85	5,394.87	1,078.97

Class	Biomass (ton) for each class			Biomass change (1985–1991)		Biomass change (1991–1996)	
	1985	1991	1996	Biomass change (ton)	Annual change (ton/yr)	Biomass change (ton)	Annual change (ton/yr)
SSa	40,956.84	14,478.66	3,708.90	-26,478.18	-4,413.03	-10,769.76	-2,153.95
SSb	339,137.73	244,108.44	148,092.30	-95,029.29	-15,838.22	-96,016.14	-19,203.23
SSc	891,081.54	1,416,009.78	939,294.81	524,928.24	87,488.04	-476,714.97	-95,342.99
SSd	3,992,275.26	3,315,566.43	3,223,158.75	-676,708.83	-112,784.81	-92,407.68	-18,481.54
Forest	6,855,343.83	4,856,145.39	3,975,738.84	-1,999,198.44	-333,199.74	-880,406.55	-176,081.31
Total	12,118,795.20	9,846,308.70	8,289,993.60	-2,272,486.50	-378,747.75	-1,556,315.10	-311,263.02

Note: Area (biomass) change = post date of area (biomass) – prior date of area (biomass)
Annual change = area (biomass) change/number of years

The multitemporal RTB or AGB images were overlaid to produce color composites for visual interpretation of vegetation change or biomass change during the periods of change detection. Figure 3 (Upper) is the RTB image color composite, in which the 1985, 1991, and 1996 RTB images were assigned as red, green, and blue, respectively. Figure 3 (Lower) is the AGB image color composite, in which the 1985, 1991, and 1996 AGB images were again assigned as red, green, and blue, respectively. The meanings of different colors in the color composites are summarized in Table 4. Figure 4 provides an example of vegetation change distribution and biomass change distribution between 1985 and 1991. From these images, it is possible to visually interpret where and how the vegetation area and biomass were changed and how much biomass was lost or accumulated during the periods of change detection.

Table 4. Meaning of Different Colors on the Change Detection Images

Color	Vegetation change (1985–1991–1996)	Biomass change (1985–1991–1996)
Red	Mature forest – non-forest – non-forest or SS1	High – 0 or very low – 0 or very low
Yellow	Mature forest – mature forest – non-forest	High – high – 0 or very low
Magenta	Mature forest or advanced SS – non-forest or SS1 – advanced SS	High – 0 or very low – middle high
Light pink	Mature forest – degraded forest or advanced SS – mature forest	High – middle high – high
Cyan	SS1 or non-forest – advanced SS – advanced SS	0 or very low – middle high – middle high
Green	Non-forest or SS1 – advanced SS – non-forest or SS1	0 or very low – middle high – 0 or very low
Blue	Non-forest – non-forest – SS	0 or very low – 0 or very low – middle high
White	Mature forests in three dates	High – high – high
Black	Non-forest areas in three dates	0 – 0 – 0

Table 5 provides the area and biomass change information for each change detection period. Between 1985 and 1991, mature forest lost 7,481 ha of area associated with 2,225,451 t of biomass loss, accounting for 11.03% of the total area and 18.36% of total biomass based on 1985 total area and total biomass results respectively. Because of fragmentation or disturbance, 6,730 ha of mature forests were degraded to different SS stages, associated with 849,527 t of biomass loss, accounting for 9.93% of total area and 7.01% of total biomass respectively. However, during this period the area of different SS stages increased by 8,488 ha that was converted from non-vegetation areas and associated with 661,314 t of biomass accumulation because of vegetation regeneration, accounting for 12.52% of the total area and 5.46% of the total biomass respectively. There were also 5,430 ha of mature forest transformed from advanced SS stages, associated with 1,020,540 t of biomass accumulation that accounted for 8.01% of the total area and 8.42% of the total biomass respectively.

A similar situation existed between 1991 and 1996. Mature forests lost 7,311 ha with 1,976,659 t of biomass loss, accounting for 10,78% of total area and 20.08% of total biomass based on 1991 total area and biomass results respectively. Because of vegetation growth, 6,848 ha of advanced SS stages transformed to mature forest, with 1,182,413 t of biomass accumulation, accounting for 10.10% of the total area and 12.01% of the total biomass. There are also 7,075 ha of non-vegetation areas converted to different SS stages with 553,769 t of biomass accumulation, accounting for 10.43% of the total area and 5.62% of the total biomass. Mature forest remained unchanged and accounted for 18.35% of the total area between 1985 and 1991, but accounted for only 15.02% of the total area between 1991 and 1996. Non-forest area increased from 24.59% in 1985–1991 to 32.05% in 1991–1996. Because of deforestation and degradation, biomass losses were 4,191,496 t (accounting for 34.59% of total biomass based on 1985) between 1985 and 1991 and 3,457,770 t (accounting for 35.12% of the total biomass based on 1991) between 1991 and 1996. However, because of vegetation growth and regeneration, biomass accumulation were 1,919,009 t (accounting for 15.83% of the total biomass based on 1985) between 1985 and 1991 and 1,901,455 t (accounting for 19.31% of the total biomass based on 1991) between 1991 and 1996. But the total biomass still lost 18.75% between 1985 and 1991 and 15.81% between 1991 and 1996. More detailed vegetation area and biomass change information can be interpreted in Table 5.

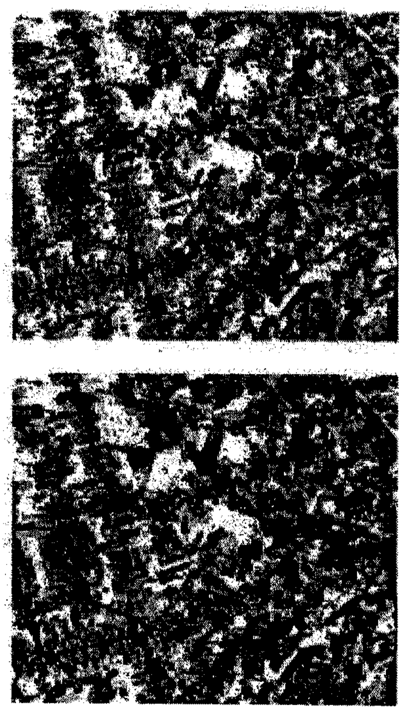


Figure 3. Multiple Dates (1985-1991-1996) of Estimated Image Color Composite: Upper is RTB Change Detection, Lower is AGB Change Detection

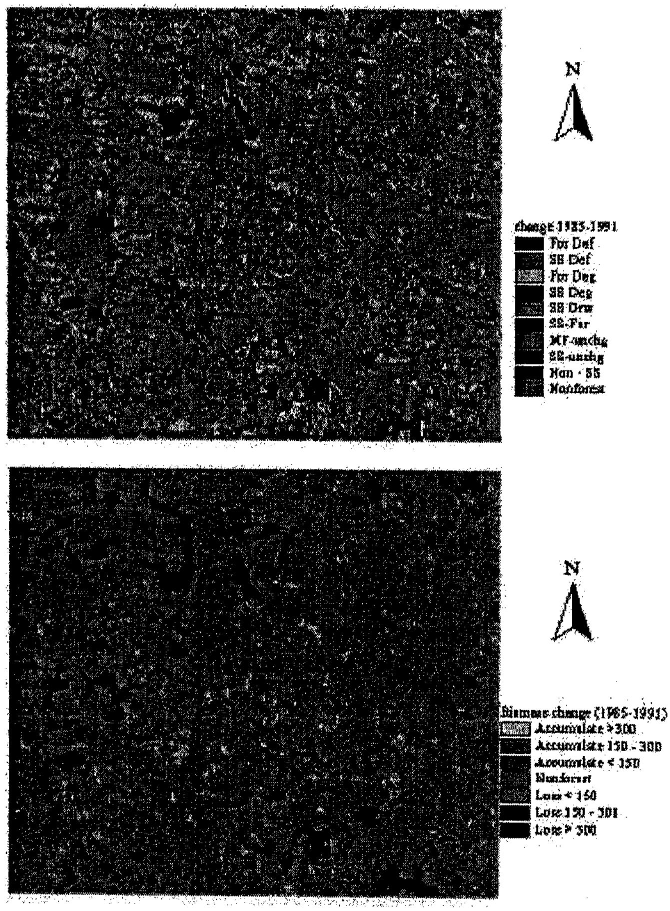


Figure 4. Vegetation Change Detection between 1985 and 1991: Upper is Area Change Detection, Lower is Biomass Change Detection

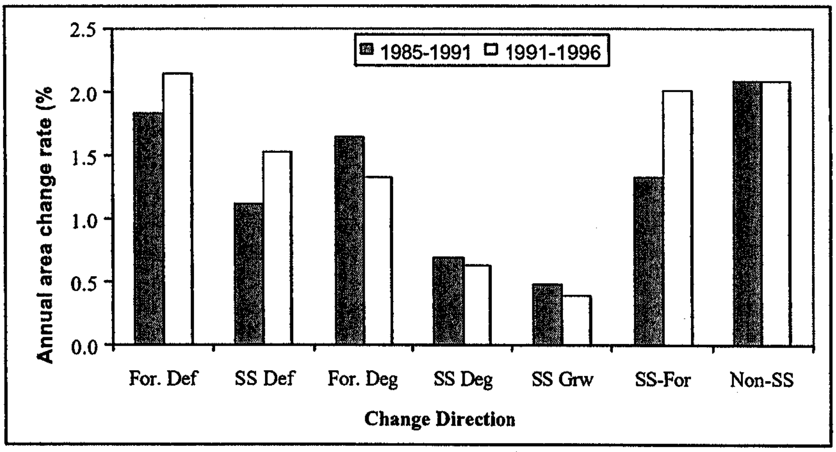
Table 5. Area and Biomass Change between 1985 and 1991 and between 1991 and 1996

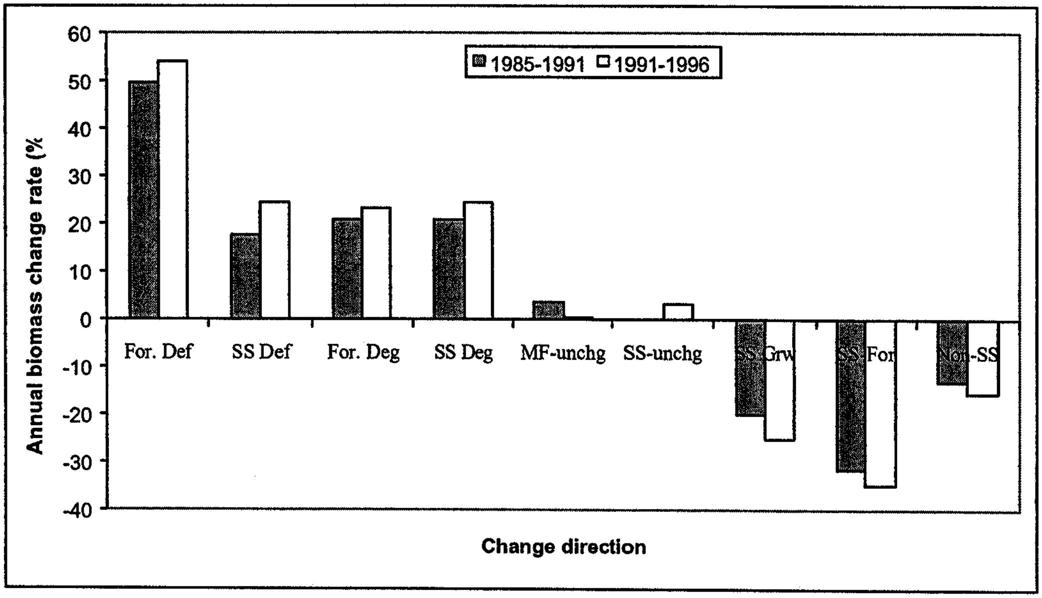
Change direction	Area and biomass change between 1985–1991					Area and biomass change between 1991–1996				
	Area (ha)	Area (%)	Biomass (ton)	Annu-biom chg (ton/yr)	Biom (%)	Area (ha)	Area (%)	Biomass (ton)	Annu-biom chg (ton/yr)	Biom (%)
For Def	7,481.43	11.03	2,225,451.33	370,908.56	18.36	7,311.15	10.78	1,976,659.47	395331.89	20.08
SS Def	4,584.51	6.76	481,587.12	80,264.52	3.97	5,167.17	7.62	634,738.05	126947.61	6.45
For Deg	6,730.20	9.93	849,527.01	141,587.84	7.01	4,532.04	6.68	525,310.38	105062.08	5.34
SS Deg	2,851.65	4.21	355,456.80	5,9242.8	2.93	2,171.97	3.20	265,224.96	53044.99	2.69
SS Grw	1,999.53	2.95	-237,155.31	-39,525.89	-1.96	1,320.84	1.95	-165,272.85	-33054.57	-1.68
SS-For	5,430.33	8.01	-1,020,539.69	-170,089.95	-8.42	6,847.83	10.10	-1,182,413.23	-236482.66	-12.01
Non-SS	8,487.72	12.52	-661,314.34	-110,219.06	-5.46	7,074.72	10.43	-553,768.84	-110753.77	-5.62
MF-unchg	12,443.49	18.35	277,685.10	46,280.85	2.29	10,183.23	15.02	31,052.43	6210.49	0.32
SS-unchg	1,116.99	1.65	1,788.48	298.08	0.01	1,465.20	2.16	24,784.65	4956.93	0.25
Non-forest	16,675.47	24.59				21,727.17	32.05			
Total	67,801.32 ha		12,118,795.20 t in 1985			67,801.32 ha		9,846,308.70 t in 1991		
Biomass loss				4,191,495.84	34.59				3,457,769.94	35.12
Biomass accumulation				1,919,009.34	15.83				1,901,454.92	19.31
Net biomass loss				2,272,486.50	18.75				1,556,315.10	15.81

Note: Area (%) = area of selected category/total area
Annu-biom chg = biomass of selected category/number of years
Biom (%) = changed biomass/total biomass of prior date
Biomass loss = the sum of changed biomass due to deforestation or degradation
Biomass accumulation = the sum of changed biomass due to vegetation growth or regrowth
Net biomass loss = biomass loss – biomass accumulation
Biomass loss rate = biomass loss/total biomass of prior date
Biomass accumulation rate = biomass accumulation/total biomass of prior date
Net biomass loss rate = net biomass/total biomass of prior date

Figure 5 provides the annual area change rates and annual biomass change rates during the periods of change detection. It shows that annual deforestation rates of mature forest and SS stages were increasing during the periods of 1985–1991 and 1991–1996, but annual degradation rates were decreasing. The SS transform rate was decreasing, but the transform rate from SS3 to mature forest was increasing during the periods of 1985–1991 and 1991–1996. The conversion rate from non-vegetation areas to different SS stages was similar during the change detection periods. The period of 1991 to 1996 had higher annual biomass loss rates than 1985–1991 due to deforestation and degradation and higher annual biomass accumulation rate due to vegetation growth and regrowth.

In the estimate RTB or AGB images, some pixels had negative RTB and AGB values, some pixels had RTB values greater than 1.0, and some pixels had unreasonably high AGB values. Checking these anomalous pixels, we found that those areas with negative RTB values were younger succession vegetation greatly affected by soil conditions and that those areas with RTB greater than 1.0 were mature forest or SS3 greatly impacted by moisture or those riverine forests. In order to improve the estimation accuracy, especially in a study area with complex biophysical environments, sufficient ground-sample inventory data are required that cover different vegetation growth stages in different environmental conditions. During development of RTB and AGB models, selecting appropriate spectral and texture signatures is critical. Because of the influence of environmental conditions such as terrain, soil, and moisture, incorporation of ancillary data into the RTB or AGB models have the potential to improve model performance. When the RTB and AGB models developed were used for vegetation change detection associated with biomass change using multiple dates of TM images, calibration of different environmental conditions between multiple dates of TM images is essential.





Note: Annual area change rate % = 100*changed area of selected category/total area/number of years.
Annual biomass change rate (t/ha yr) = changed biomass of selected category/changed area of the same category/number of years

Figure 5. Comparison of annual change rate of vegetation change direction: Upper shows annual area change rates, Lower shows annual biomass change rates

Accuracy assessment is very important for better understanding the developed results and better use of the results for making decisions. Different accuracy assessment methods were used (e.g., overall accuracy, producer's and user's accuracy, and kappa analysis) and the issues of accuracy in remote sensing were discussed (Congalton, 1991, Jensen, 1996, Biging et al., 1999). However, accuracy assessment was not fully implemented in this research due to limited ground-truth data. Visually interpreting the change detection image confirmed that the vegetation change detection based on RTB approach was successful, and the RTB approach was a promising method for successional and mature forests change detection in the Amazon basin. Also this research can start to answer some key questions about the role of successional forests in carbon emission due to deforestation. This study focused on vegetation change associated with biomass change, and, provided these results can be linked to carbon data to explore how the mature forest deforestation and regrowth affect the carbon emission and uptake. This is an important finding to illustrate the role of understanding land-use dynamics in the region and to share that deforestation processes are key components of the regional carbon cycle.

CONCLUSIONS

The RTB approach proved feasible to implement vegetation change detection. It has the following advantages over the traditional classifications and change detections that are based on training sample data: (1) RTB values reflect stand structures of different vegetation classes; (2) a classification does not require a large selection of training sample data, and the results are less sensitive to whether the ground-truth data are fully representative of features of interest; (3) the RTB approach is sufficiently flexible for reclassification based on the characteristics of the study area; and (4) multitemporal RTB images are suitable to implement vegetation change detection. Therefore, the RTB thresholding method implemented is more appropriate to use for classification and change detection of different vegetation growth stages, especially in the Amazon basin. This approach is valuable in the LBA project because of the complex stand structure, landscape, species composition, and difficulty in collecting ground-truth data in the Amazon basin. Multitemporal RTB images derived from TM images can produce detailed vegetation change detection, and multitemporal AGB images combined with an RTB change detection image can develop biomass change detection for each vegetation change direction. The methodological structure for vegetation area and biomass change detection developed in this research was successfully implemented in a moist tropical region in the Brazilian Altamira region. This study puts forward a promising method for vegetation change detection and provides good area and biomass change estimates.

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