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INTEGRATION OF VEGETATION INVENTORY DATA AND THEMATIC MAPPER IMAGE FOR AMAZONIAN SUCCESSIONAL AND MATURE FOREST CLASSIFICATION

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ABSTRACT

Successional and mature forest classification is often difficult in moist tropical regions. This paper explores vegetation stand structures of successional and mature forests and their spectral characteristics. Canonical discriminant analysis (CDA) was used to identify important stand parameters for secondary succession and mature forest classification. Correlation coefficient was used to analyze different stand parameter relationships and associated TM spectral signatures. Transformed divergence was used to analyze the separability of succession stages and mature forest based on the resultant images from CDA and principal component analysis (PCA), respectively. This study indicates that five vegetation categories, i.e., initial succession, intermediate succession, advanced succession, small biomass mature forest, and large biomass mature forest, can be distinguished based on vegetation stand features using field measurements, but some of them are difficult to be classified using TM data. Tree diameter at breast height, tree height, aboveground biomass, and ratio of tree biomass to total aboveground biomass are the best stand parameters distinguishing vegetation classes. Bands TM 4 and TM 5 are best for distinguishing vegetation classes. The transformation using CDA improved separability of vegetation classes, but not using PCA. Two successional stages and one mature forest class are suitable in this study area.

INTRODUCTION

Many research projects involved in Amazon basin require accurate delineation of different secondary succession stages over large regions/subregions to delineate trajectory of land-use/land-cover change and carbon dynamics. For example, accurate estimation of carbon change rates following deforestation or afforestation requires successional stage information associated with biomass. In previous research different approaches have been used to identify successional stages. The most straightforward method is based on the vegetation age (Uhl et al., 1988; Saldarriaga et al., 1988). However, successional forest stands can be significantly influenced by land-use history (Uhl et al. 1988), soil fertility (Moran et al., 2000a; 2000b), original vegetation, and clearing size (Tucker et al., 1998). Age alone cannot be used to predict successional stages since many factors can strongly affect structural characteristics within the same age class. Moran and Brondízio (1998) and Moran et al. (2000a) defined regrowth stages of Amazônian tropical forest based on the analysis of average stand height and basal area. They found that stand height was a significant discriminator of regrowth in initial (SS1), intermediate (SS2), and advanced (SS3) succession. Tucker et al. (1998) analyzed physiognomic characteristics in two different Amazônian sites to classify successional stages. They found that the central discriminating factor was the contribution of saplings and trees to the total basal area of the successional forest. Sapling/tree basal area relations can help predict other structural features and effectively differentiate successional stages.

In the Amazon basin, remote-sensing technology also has been used to analyze land cover or secondary succession classification and deforestation detection for the past decade (Lucas et al., 1993; Mausel et al., 1993; Foody and Curran, 1994; Li et al., 1994; Moran et al., 1994a; 1994b; Brondizio et al., 1994; Adams et al., 1995; Brondizio et al., 1996; Foody et al., 1996; Steininger, 1996; Rignot et al., 1997; Saatchi et al., 1997; Yanasse et al., 1997; Moran and Brondizio ,1998; Roberts et al., 1998; McCracken et al., 1999; Lu, 2001; Lu et al., 2002; Lucas et al., 2002). Much previous research focusing on moist tropical forest using remotely sensed data has not provided the successional subclass information due to the complexity of biophysical factors and landscape (Lucas et al. 1993; Foody and Curran, 1994; Adams et al., 1995; Foody et al., 1996; Steininger, 1996; Rignot et al., 1997; Roberts et al., 1998; Lucas et al., 2002). Because of the importance in delineating succesional subclasses, our research group has explored to classify successional forests into three stages. For example, supported by abundant and accurate field measurements from all classes of interest, Mausel et al. (1993) analyzed Landsat Thematic Mapper (TM) spectral responses of different successional stages and classified the vegetation into SS1, SS2, SS3 and mature forest using an Extraction and Classification of Homogeneous Objects (ECHO) classifier. Similar studies were conducted by Moran et al. (1994a), Li et al. (1994), and Brondizio et al. (1996). However, the classification accuracy greatly depends on the availability and quality of a very large number of training data sets. Confusion often occurs between degraded pasture and SS1, between different successional stages, and between advanced successional and mature forests, since there is no clear distinction between vegetation growth stages. The canopy structure of advanced successional and mature forest can be very similar although they have significantly different ages and aboveground biomass.

Although successful methods have been used to identify vegetation classes in the Amazon basin, the following problems have remained: (1) which vegetation stand parameters are most appropriate to identify vegetation types? Different authors and different study areas still use different methods to group successional stages, leading to difficulty in implementing comparative analysis among different areas; (2) what relationships exist between vegetation stand parameters and TM reflectance? Better understanding such relationships is conducive to finding appropriate TM bands for estimation of vegetation stand parameters or for vegetation classification; (3) can vegetation classes that are grouped based on field measurements be separated on TM imagery? This paper attempts to answer these questions through exploring vegetation characteristics and linking vegetation measurements with TM reflectance in the Rondônia region of the Brazilian Amazon.

METHOD

Description of the Study Area

Rondônia has experienced high deforestation rates in the Brazilian Amazon during the past decade (INPE, 2002). Following the national strategy of regional occupation and development, colonization projects initiated by the Brazilian government in the 1970s played a major role in this process (Moran, 1984; Schmink and Wood, 1992). Most colonization projects in the state were designed to settle landless migrants. The data used in this study were collected in Machadinho d'Oeste in northeastern Rondônia. Settlement began in this area in the mid-1980s, and the immigrants transformed the forested landscape into a patchwork of cultivated crops, pastures, and a vast area of fallow land. The terrain is undulated, ranging from 100 to 450 m above sea level. Settlers, rubber tappers, and loggers inhabit the area, transforming the landscape through their economic activities and use of resources.

Field Data Collection

Fieldwork was carried out during the dry seasons of 1999 and 2000. The procedure used for surveying vegetation was a multilevel technique adapted from methods used at the Center for the Study of Institutions, Population, and Environmental Change (CIPEC, 1998). The surveys were carried out in areas with relatively homogeneous ecological conditions (i.e., topography, distance from water, and land use) and uniform physiognomic characteristics. After defining the area to be surveyed (plot sample), three subplots (1 m^2, 9 m^2, and 100 m^2) were randomly installed to cover the variability within the plot sample. The center of each subplot was randomly selected. Seedlings were defined as young trees or shrubs with a stem diameter smaller than 2 cm. Saplings were defined as young trees with a stem diameter greater than 2 cm and DBH smaller than 10 cm. Trees were defined as woody plants with a DBH greater than or equal to 10 cm. Height, stem height, and DBH were measured for all trees in the 100 m^2 area. Height and DBH were measured for all saplings in the 9 m^2 area. Ground-cover estimation and individual counting were carried out for seedlings and herbaceous vegetation in the 1 m^2 area. Every plot was registered with a Global Positioning System (GPS) to allow further integration with spatial data in Geographic Information Systems (GIS) and image processing systems. Forty sample plots and 120 subplots were inventoried, covering successional and mature forests.

Data Analysis

A database was built to integrate all vegetation data collected during fieldwork. Vegetation stand parameters—tree/sapling DBH, tree/sapling height, tree/sapling basal area, tree/sapling density, tree/sapling biomass, total basal area, total biomass, ratio of tree biomass to total biomass (RTB), and ratio of tree basal area to total basal area (RTBA)—were calculated for each plot. The individual vegetation biomass was calculated using Equ. [1] for trees (DBH ≥ 10 cm) (Brown et al., 1995) and Equ. [2] for saplings (2 cm ≤ DBH < 10 cm) (Honzák et al., 1996).

$$YT = 0.0326 \cdot (DT)^2 \cdot H \quad \text{and} \qquad [1]$$

$$YS = \exp[-3.068 + 0.957 \ln (DS^2 \cdot H)], \qquad [2]$$

where DT and DS are the tree DBH and sapling diameter in centimeters, respectively; H is the total tree or sapling height in meters; and YT and YS are the individual tree and sapling biomass in kilograms, respectively. Above-ground biomass (AGB) is then calculated through Equ. [3].

$$AGB = \sum_{i=1}^{m} YT_i \,/AT + \sum_{j=1}^{n} YS_j \,/AS, \qquad [3]$$

where m is the total tree number in the sample plot, and n is the total sapling number in the subplot. AT and AS are the areas of sample plot and subplot in square meters, respectively, and AGB is the above-ground biomass (kg/m^2).

Caution should be taken when analyzing above-ground biomass estimations as they are dependent on several variables such as hollowness, wood density for every species, bark, presence of palms, vines, and dead biomass (Fearnside, 1992). For large trees with DBH greater than 60 cm, a correction factor based on an average wood density was adopted (Fearnside, 1997).

As a preliminary baseline, maximum heights of 8, 10, and 12 m, and maximum ages of 5, 10, and 15 years were suggested for SS1, SS2, and SS3, respectively. These numbers were assigned by approximation to designate the stands to be surveyed, not necessarily indicating real boundaries between regrowth stages. The mature forest consisted of small biomass mature forest (SMF) and large biomass mature forest (LMF) based on AGB. The vegetation category (SS1, SS2, SS3, SMF, or LMF) is selected as a dependent variable and vegetation stand parameters (e.g., tree DBH, tree height, tree biomass, etc.) as independent variables. Canonical Discriminant Analysis (CDA) is used to refine vegetation classification results and to identify important stand parameters that can be effectively used to distinguish vegetation classes. The implementation of CDA provides some important information for classifying sample plots and identifying important parameters (Huberty, 1994; Markin, 1996). For example, the eigenvalues show how much of the variance in the dependent variables is accounted for by each function. Relative percent of variance indicates how many functions are important. Wilks' Lambda is used to test the significance of each discriminant function, specifically the significance of the eigenvalue for a given function. It measures the difference between groups of the centroid (vector) of means on the independent variable. The smaller the Wilks' Lambda, the greater the difference, and the more important the independent variable is to the discriminant function. Canonical correlation (R) measures the association between the groups formed by the dependent variable and the given discriminant function. Larger R value indicates high correlation between the discriminant function and the groups (McGarigal et al., 2000). The application of CDA in this research is to identify the important vegetation parameters for delineation of successional and mature forests.

TM data (the acquisition date was on June 18, 1998) were radiometrically calibrated and atmospherically corrected into apparent reflectance using an image-based dark object subtraction (DOS) model (Chavez, 1996; Lu et al., 2002). The path radiance was identified based on clear water for each band. The image was geometrically rectified using control points taken from topographic maps at 1:100,000 scale (UTM, south 20 zone). Nearest-neighbor resampling technique was used and a root mean squared error (RMSE) of smaller than 0.5 pixel was obtained. Because each sample plot has UTM coordinates provided by GPS devices during fieldwork, it can be accurately linked to TM imagery. Therefore, TM reflectance of each plot can be retrieved and related to vegetation stand parameters. A 3x3 window size was used to extract the mean value of image data for each plot. In addition to the forty plots used for vegetation measurements, there are also lots of sites covering different successional and mature forests were identified during the field work. All these plots were linked to TM image to extract the image data. In order to compare the performance of CDA method in improving successional forest classification, PCA and original TM data were also tested. Pearson's correlation coefficient was used to explore the relationships between vegetation stand parameters and TM reflectance. Reflectance curves were used to explore the spectral characteristics of successional and mature forests. Transformed divergence (TD) was used to analyze the separability among different vegetation classes.

RESULTS

Analysis of Vegetation Stand Structure

As indicated in previous section, preliminary three successional stages (i.e., SS1, SS2, and SS3) were assigned based on vegetation age and two mature forest classes (i.e., SMF and LMF) based on AGB. The results from CDA indicated that misclassification occurred in some successional subclasses based on age due to the impacts of soil conditions and land use history. However, the misclassified classes can be adjusted through the CDA projection, until all plots were assigned a suitable successional subclass. Then the CDA results were used to identify the independent variables that most effectively distinguished vegetation classes. Table 1 shows that total/tree biomass, total/tree basal area, RTB, RTBA, tree DBH, and tree height are the best stand parameters because they have small Wilks' Lambda values. The correlation coefficient between a given independent variable and the discriminant score associated with a given discriminant function indicates that total/tree biomass, total/tree basal area, tree DBH, and tree height have high correlation with CDA function 1. The RTB and RTBA have high correlation with CDA function 2. However, not all the important parameters mentioned above are necessary for distinguishing vegetation classes because some parameters are strongly related to each other. For example, AGB is strongly related to tree biomass (0.83) and total basal area (0.80). Total basal area is strongly related to tree basal area (0.81). The RTB is strongly related to RTBA (0.98), sapling basal area (-0.90), sapling biomass (-0.88), and sapling density (-0.81). The RTBA is also strongly related to sapling basal area (-0.91), sapling biomass (-0.88), and sapling density (-0.83). This indicates that RTB or RTBA is sensitive to sapling characteristics. Analysis of correlation coefficients between discriminating variables and discriminant functions and between the vegetation stand parameters indicates that CDA function 1 provides the tree or canopy information and CDA function 2 provides sapling or understory information. Tree DBH, tree height, AGB, and RTB are the best stand parameters; however, sapling stand parameters are less important in distinguishing vegetation classes.

Table 1. Wilks' Lambda and Correlation Coefficients between Discriminating Variables and Discriminant Functions

Variables	Correlation coefficient F1	F2	F3	F4	Wilks' Lambda
Above-ground biomass (AGB)	.632	-.184	-.103	-.424	0.074
Tree DBH (T_DBH)	.257	.123	.246	.090	0.313
Tree density (T_Dens)	.103	.170	-.434	-.407	0.569
Total basal area (TO_BA)	.323	-.073	-.341	-.293	0.232
Tree biomass (T_Bio)	.545	-.139	-.037	-.601	0.098
Sapling density (S_Dens)	-.104	-.142	-.240	.592	0.617
Tree basal area (T_BA)	.344	-.028	-.214	-.530	0.214
Sapling biomass (S_Bio)	-.025	-.028	-.091	.443	0.941
Sapling basal area (S_BA)	-.066	-.067	-.179	.422	0.817
Ratio of T_BA to TO_BA (RTBA)	.242	.281	.059	-.378	0.279
Ratio of T_Bio to AGB (RTB)	.245	.315	.045	-.357	0.262
Sapling height (S_H)	.074	.029	.074	.356	0.836
Tree height (T_H)	.252	.173	.220	-.292	0.306
Sapling DBH (S_DBH)	.020	.085	.129	-.168	0.910

Implementation of CDA based on sample plots indicates that significant separability exists between different SS stages, SMF, and LMF, although the process of vegetation growth is continuous. Figures 1, 2, and 3 illustrate the characteristics of vegetation stand parameters (i.e. DBH, height, density, and biomass). Basal area and RTB (or RTBA) are ignored, because basal area is strongly related to biomass and RTB (or RTBA) is strongly related to sapling parameters such as biomass, basal area, and density.

Tree DBH and tree height increased rapidly from SS1 to SS3 (Figure 1). The tree height and tree DBH between SMF and LMF were somewhat overlapped although their biomass amounts varied. There were also some overlaps of tree height between SS3 and SMF. Sapling DBH did not change significantly, but sapling height increased slightly from SS1 to SS3. The sapling DBH and height slightly increased from SMF to LMF, but they are very similar between SS3 and SMF.

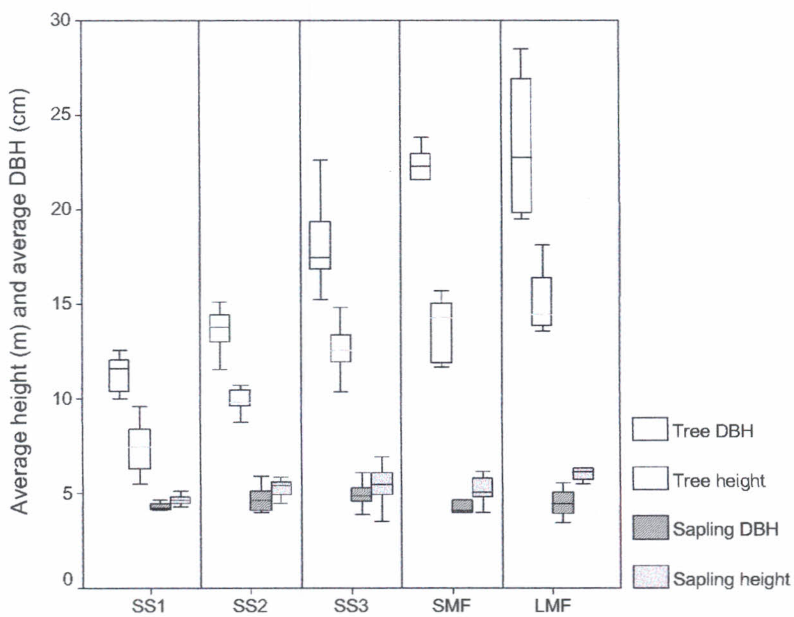

Figure 1. Vegetation DBH and Height Characteristics of Different Vegetation Growth Stages

Tree density increases rapidly from SS1 to SS2 (Figure 2) but stays relatively stable after SS2. Sapling density decreases rapidly from SS1 to SS3. The tree and sapling density in SMF were smaller than in LMF. As vegetation grows, trees increase in density and start to dominate the canopy after SS2 stage. The understory (mainly saplings and seedlings) decreases due to vegetation competition for sun energy, soil nutrients, water, etc. This usually occurs from SS1 to SS2. After entering SS3, vegetation forms different layers of stand structures, from canopy to understory. A special microenvironment is formed that is more suitable for interaction between soil nutrients and vegetation biomass after entering the SS3 stage. Therefore, after SS3, vegetation density stays relatively stable although vegetation still grows.

Biomass is related to vegetation stand DBH, height, and density. The above-ground tree biomass and total biomass have similar trends, i.e., they increase constantly from SS1 to SS3 and reach the highest levels in mature forest (Figure 3). The higher variability of biomass in mature forest is related to its larger range in DBH and height in this stage than in stages of regrowth. Sapling biomass decreases from SS1 to SS3, especially from SS2 to SS3. From SS3 to mature forest, sapling biomass does not change significantly.

Biomass change during the progression through successional stages is significantly related to the change of vegetation density. At the successional stages, biomass is more strongly related to the sapling parameter change, while among SS3, SMF, and LMF, biomass change is weakly associated with vegetation density, but strongly related to tree DBH and tree height growth. So, at the advanced successional stage and mature forest, biomass change is more strongly related to changes in tree parameters.

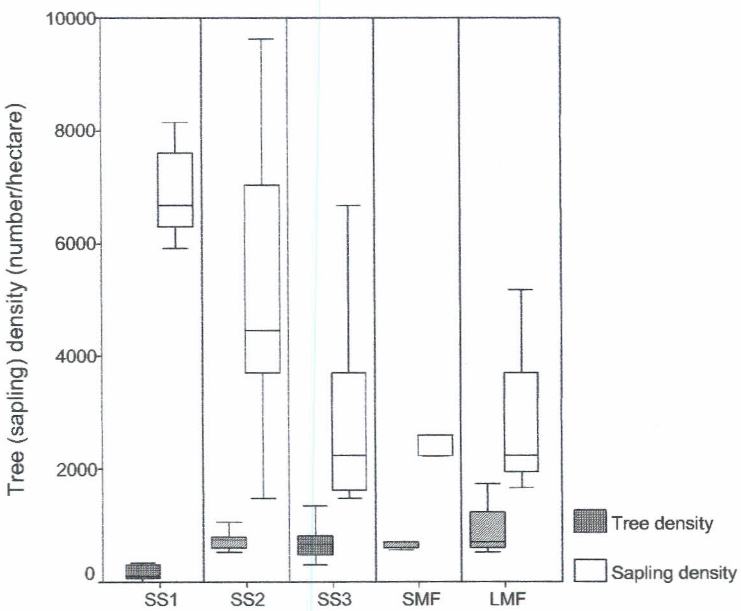

Figure 2. Vegetation Density Characteristics of Different Vegetation Growth Stages

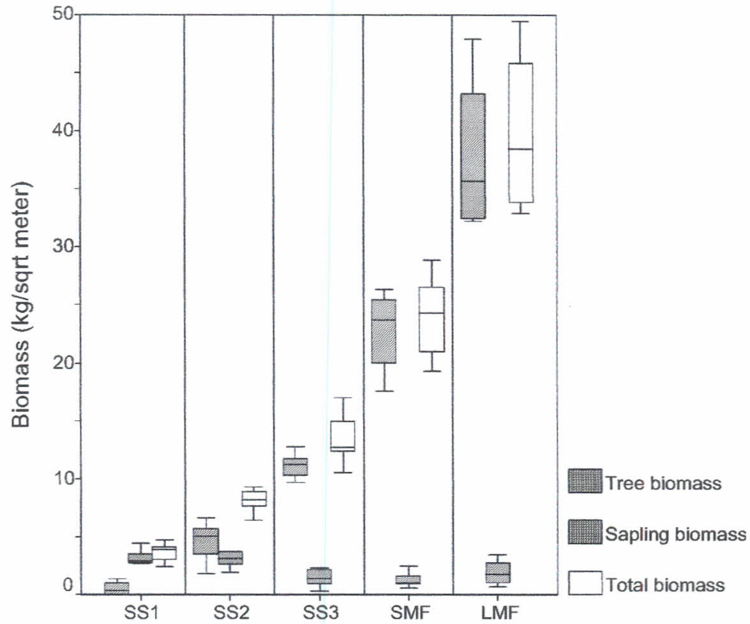

Figure 3. Biomass Characteristics of Different Vegetation Growth Stages

Characteristics of Successional Stages and Mature Forest

The first two years of SS1 are characterized by overall dominance of grasses, herbaceous plants, vines, and saplings. This dense ground structure is progressively usurped by saplings during and after the second year. In SS1, herbaceous plants, seedlings, and saplings together are responsible for over 90 percent of total biomass, with a vertical structure characterized by a full profile of saplings and herbaceous plants. Few trees can reach 10 cm DBH at this stage. Saplings are the main structure element and represent the majority of the above-ground biomass. The biomass is less than 5 kg/m^2 with age ranging from 1 to 5 years.

Saplings still account for most of the biomass in SS2, which ranges from 6 to 10 kg/m^2. Tree DBH can reach 15 cm, and tree height can reach 10 m. The age can be between 4 and 10 years, depending on land-use history and soil fertility at the site. Vegetation structure provides a mix of dense ground cover of saplings and young trees with higher canopy than SS1 and very small internal difference between canopy and understory individuals. SS2 is characterized by a lack of stratification between canopy and understory.

Trees occupy the canopy and present obvious stratification of forest stand structure in SS3. Sapling and seedling biomass greatly declines because the tree canopy leads to reduced growth of saplings and seedlings. The biomass ranges from 10 to 17 kg/m^2, tree DBH ranges from 15 to 19 cm, tree height ranges from 10 to 15 m, and age is over 8 years. In this stage, there is a major shift in structure that differentiates understory from canopy individuals; that is, the presence of saplings is less significant than that of trees. One can find differences between the canopy and understory in terms of height and density of individuals at both levels. SS3 presents a less continuous vertical profile and a clear distinction between dominant trees and less dense saplings.

In the mature forest, above-ground biomass and vegetation density can be different depending on soil conditions, species composition, and topography at the site. Some mature forests have tree DBH, tree height, and above-ground biomass similar to SS3. In this study we call such a mature forest SMF to separate it from LMF. In SMF, biomass ranges from 12 to 19 kg/m^2, average tree DBH ranges from 17 to 24 cm, and average tree height ranges from 11 to 15 m. In a typical mature forest, trees account for the majority of above-ground biomass, reaching over 90 percent. Biomass is greater than 20 kg/m^2, some even as high as 50 kg/m^2. In this stage, large trees occupy the canopy. Trees with DBH of 25 to 30 cm dominate, and a considerable number of individuals have a DBH over 40 cm. Many tree individuals are taller than 17 m, and some between 25 and 30 m are present, followed by a few scattered individuals over 35 m tall or emergent.

Linking Vegetation Stand Parameters and TM Reflectance

TM reflectance mainly captures vegetation canopy information. The reflectance values can be significantly altered by different vegetation stand structures. Such structural allocation is related to different stand parameters such as DBH, height, biomass, and density. So what relationships exist between vegetation stand parameters and TM reflectance? The correlation coefficients between stand parameters and TM refelctane (Table 2) indicate that:

(1) TM reflectance is more strongly related to tree stand parameters (such as tree DBH, tree height, tree biomass) than to sapling stand parameters, except for sapling vegetation density. This means that TM reflectance mainly responds to tree stand information or canopy information but weakly to sapling information.

(2) Bands TM 4 and TM 5 are better related to vegetation stand parameters than the other TM bands because TM 4 and TM 5 have higher vegetation reflectance and larger standard deviations than the other TM bands have.

(3) TM reflectance is negatively related to tree stand parameters but positively related to sapling basal area and sapling density. This is because the impact of canopy shadows on the TM reflectance increases as vegetation growth leads to complex stand structure.

(4) TM 4 is more strongly related to tree stand parameters such as tree DBH and tree height, but TM 5 is more strongly related to comprehensive vegetation stand parameters such as total vegetation biomass and total basal area. This indicates that TM 4 is possibly more suitable for tree DBH and tree height estimation, while TM 5 is more suitable for biomass and basal area estimation.

(5) RTB and RTBA are strongly related to TM reflectance, especially with TM 4 and TM 5. Therefore, some sapling information can be indirectly derived from this relationship because RTB or RTBA is strongly related to sapling density and sapling biomass.

Table 2. Correlation between Vegetation Stand Parameters and TM Bands

Band	T_DBH	T_H	T_BA	T_Bio	S_DBH	S_H	S_BA	S_Bio	TO_BA	AGB	RTBA	RTB	T_dens	S_dens
TM 1	-.523*	-.428*	-.289	-.424*	-.049	-.397†	.102	-.065	-.286	-.455*	-.258	-.25	.190	.151
TM 2	-.780*	-.647*	-.562*	-.597*	-.091	-.212	.425*	.235	-.482*	-.580*	-.623*	-.615*	-.110	.510*
TM 3	-.726*	-.640*	-.513*	-.543*	-.003	-.261	.465*	.251	-.415†	-.521*	-.593*	-.569*	-.066	.517*
TM 4	-.870*	-.745*	-.668*	-.740*	-.067	-.274	.447*	.243	-.593*	-.728*	-.692*	-.680*	-.130	.548*
TM 5	-.810*	-.740*	-.694*	-.755*	-.044	-.283	.425*	.221	-.628*	-.748*	-.670*	-.660*	-.195	.504*
TM 7	-.707*	-.642*	-.663*	-.681*	-.006	-.201	.459*	.267	-.583*	-.663*	-.659*	-.642*	-.273	.514*

*Correlation is significant at the 0.01 level; † Correlation is significant at the 0.05 level.

Previous analysis indicates that tree stand parameters are strongly associated with TM bands, and five vegetation categories can be grouped based on these parameters. Can these named categories be separated using TM imagery? Figure 4 illustrates the reflectance curves of different vegetation categories. SMF has different reflectance from SS3, especially in TM 4 and TM 5. The main difference between SS3 and SMF is in vegetation density and species composition. However, SMF has reflectance similar to that of LMF despite their differences in vegetation biomass. This is because SMF and LMF have similar vegetation stand structure, leading to similar reflectance in TM data. Another reason is the reflectance saturation due to limited radiometric resolution. On the other hand, SS1 has a similar reflectance curve to that of SS2 because SS1 and SS2 do not have clear stratification of vegetation stand structure. The reflectance in SS3, SMF, and LMF can be reduced due to the canopy shadows caused by complex vegetation stand structure. In general, SS1 has the highest reflectance and LMF has the lowest reflectance in each TM band. The vegetation reflectance decreases as vegetation growth results in increasing canopy shadow effects.

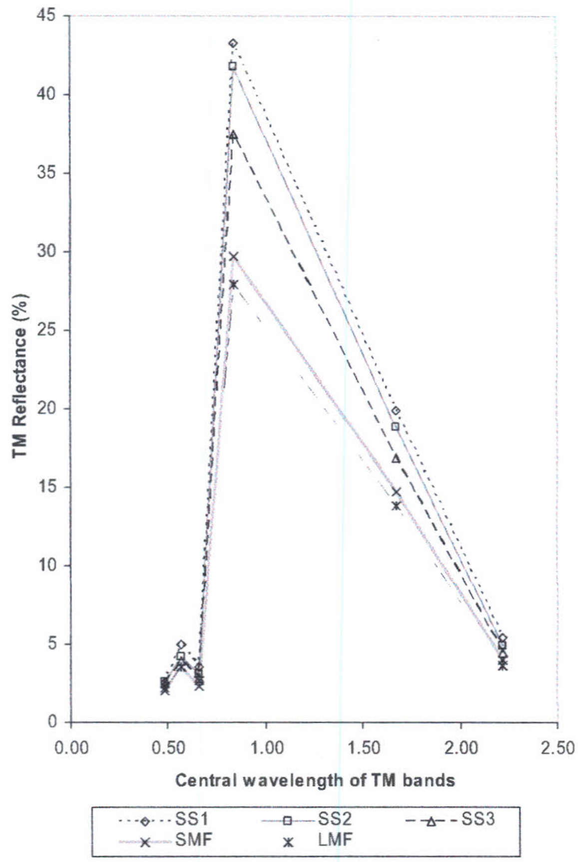

Figure 4. TM reflectance Characteristics of Vegetation Growth Stages

Spectral Characteristics of Vegetation Classes

CDA is one of the linear transform methods that can specifically extract vegetation information based on the separability of sampled classes. The sampled reflectance values of different TM bands are selected as independent variables, the vegetation category—SS1, SS2, SS3, SMF, and LMF —is selected as a dependent variable, and the CDA algorithm is implemented. The first CDA function accounts for 97.4 percent of the total variance and has strong correlation with the dependent variable (R = 0.99). Table 3 indicates that bands TM 4 and TM 5 are the two most important bands in differentiating vegetation classes because they have the smallest Wilks' Lambda (0.043 and 0.087, respectively) and highest correlation coefficients (0.532 and 0.371, respectively) with the first CDA function. Band TM 2 has smaller Wilks' Lambda value than those of bands TM 1, TM 3, and TM 7. Band TM 4 and TM 2 are significantly correlated to CDA function 2. The correlations between TM bands and CDA functions indicate that bands TM 1, TM 3, and TM 7 are least important because they have high Wilks' Lambda values and are weakly related to the first and second CDA functions, TM 4, TM 5, and TM 2 are important bands for the separability of vegetation classes.

The coefficients and constant used for the linear transform of TM bands based on CDA indicate that CDA function 1 is the difference between high vegetation reflectance bands (TM 4, TM 5, and TM 2) and lower vegetation reflectance bands (TM 1, TM 3, and TM 7). The CDA function 1 extracts more vegetation information from TM 4, TM 5, and TM 2. It has the potential to improve the separability between vegetation classes because it enhances the difference of vegetation through linear transform of TM bands.

Table 3. Wilks' Lambda, Correlation Coefficients, and Discriminant Function Coefficients

	Correlation Coefficients			Wilks' Lambda	Discriminant Function Coefficients		
TM	F1	F2	F3		F1	F2	F3
TM 1	0.093	0.290	0.318	0.543	-5.702	2.747	0.538
TM 2	0.211	-0.365	0.811	0.206	7.747	-6.046	-0.707
TM 3	0.141	-0.010	0.967	0.343	-3.865	3.821	3.972
TM 4	0.532	0.745	-0.043	0.043	0.461	0.297	-0.046
TM 5	0.371	0.212	0.060	0.087	3.018	-0.443	-0.323
TM 7	0.204	-0.105	0.113	0.240	-4.383	0.150	-0.141
Constant for Discriminant Functions					-54.014	2.683	-2.355

Table 4 provides the transformed divergence values between the vegetation classes. It indicates that CDA method improved the separability of vegetation classes compared to the original TM bands. PCA has limited improvement in their separability. CDA mainly improved the separability between successional stages and between advanced successional and mature forest. However, the distinction between SS1 and SS2, between SMF and LMF is still difficult although CDA method can improve the classification performance. It is suitable to merge the SS1 and SS2 into one class, and SMF and LMF as one class.

Table 4. Comparison of Transformed Divergence among Different Image Processing Methods.

Data sets	Avg TD	Class pairs 1:2	1:3	1:4	1:5	2:3	2:4	2:5	3:4	3:5	4:5
CDA	1451	568	1531	1984	1998	887	1878	1974	1256	1730	708
PCA	1394	361	1497	1996	1998	965	1965	1985	1358	1621	191
TM	1349	431	1410	1941	1988	884	1761	1938	1093	1563	482

Note: In class pairs, 1 – SS1; 2 – SS2; 3 – SS3; 4 – SMF; 5 – LMF

DISCUSSION

In our study, the sample variability allowed the comparison of vegetation structure and spectral responses within and across classes. In general, tree DBH, tree height, biomass, and RTB are good indicators of vegetation regrowth stages. SS1, SS2, SS3, SMF, and LMF can be classified based on field measurements. It is important to mention that many of these parameters are significantly correlated, indicating that less sampling effort would be needed to depict different classes of succession in studies at the regional scale. As other studies have shown, height or DBH of trees could be chosen in this case to represent stages of regrowth (Moran et al. 2000b). The advantage of choosing these parameters instead of basal area or biomass is the relative simplicity of directly measuring them during fieldwork and indirectly, in the near future, by the use of LIDAR.

Despite the clear separation among the classes of succession and forest, when graphed against mean reflectance in TM bands, just three clusters of samples were well differentiated: SS1 and SS2 together, SS3, and SMF and LMF together. These results indicate that three vegetation types are appropriate when only original TM imagery is used for classification. However, selection of a proper linear transform of TM bands can improve the separability between vegetation classes. This study implies that linear transforms, for which the transform coefficients are specifically derived from the integration of field measurements and TM spectral data, have the potential to improve classification accuracy.

TM reflectance mainly represents canopy information. Different vegetation stand structure will influence the reflectance values. SS1 and SS2 have similar reflectance because the vegetation in these stages does not have clear stratification of vegetation structures, while SS3, SMF, and LMF have clear stratification. Canopy shadows can reduce the vegetation reflectance significantly. In particular, the complexity of vegetation stand structure in SMF and LMF results in similar reflectance values. Vegetation growth increases the effects of canopy shadows on a TM image. When vegetation grows to a certain age or vegetation stand reaches a certain structure, TM reflectance is possibly saturated although biomass may still be increasing. This is especially obvious in SMF and LMF. This problem induces difficulty in accurately estimating vegetation stand parameters (e.g., biomass) when TM imagery is used for estimating advanced successional or mature forest stand parameters. This problem can also reduce classification accuracy because of the reflectance similarity between SS3 and mature forest. In this case, other sensor data such as radar image will be helpful because it can penetrate and capture more information from below classifications.

CONCLUSION

This study indicates that Amazônian vegetation can be grouped into five categories—SS1, SS2, SS3, SMF, and LMF—according to vegetation stand characteristics. Tree DBH, tree height, biomass, and RTB are the most useful stand parameters for identification of vegetation categories.

TM reflectance is better related to tree stand parameters than understory parameters. TM 4 and TM 5 are the best bands for differentiation of successional stages and mature forest, but TM reflectance is difficult to distinguish SS1 from SS2 and SMF from LMF. Two successional stages and one mature forest class are suitable in this study area. CDA transform has the potential to improve separability of successional stages.

The results of this research can be helpful in (1) identifying successional stages based on tree DBH, tree height, biomass, and RTB individually or in combination; (2) determining how many classes of successional vegetation can be distinguished in the Amazon basin using remote-sensing data; (3) selecting appropriate TM bands for estimation of vegetation stand parameters (e.g., DBH, height, biomass) using TM imagery; and (4) improving classification accuracy through linear transform of TM bands based on CDA.

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