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Land-cover classification in the Brazilian Amazon with the integration of Landsat ETM+ and Radarsat data

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Land-cover classification with remotely sensed data in moist tropical regions is a challenge due to the complex biophysical conditions. This paper explores techniques to improve land-cover classification accuracy through a comparative analysis of different combinations of spectral signatures and textures from Landsat Enhanced Thematic Mapper Plus (ETM+) and Radarsat data. A wavelet-merging technique was used to integrate Landsat ETM+ multispectral and panchromatic data or Radarsat data. Grey-level co-occurrence matrix (GLCM) textures based on Landsat ETM+ panchromatic or Radarsat data and different sizes of moving windows were examined. A maximum-likelihood classifier was used to implement image classification for different combinations. This research indicates the important role of textures in improving land-cover classification accuracies in Amazonian environments. The incorporation of data fusion and textures increases classification accuracy by approximately 5.8–6.9% compared to Landsat ETM+ data, but data fusion of Landsat ETM+ multispectral and panchromatic data or Radarsat data cannot effectively improve land-cover classification accuracies.

1. Introduction

Accurate image classification describing spatial distribution and patterns of land cover is a prerequisite for many research topics and applications, such as landscape characterization, land-cover change analysis, input into different models for analysis of carbon cycles, habitat suitability and risk of land degradation. Many efforts and progresses have been made to improve the land-cover or vegetation classification performance, for example, use of subpixel information based on spectral mixture analyses (Adams *et al.* 1995, Roberts *et al.* 1998, Lu *et al.* 2003b), use of non-parametric classifiers such as neural networks (Paola and Schowengerdt 1995, Atkinson and Tatnall 1997, Kavzoglu and Mather 2004) and decision trees (Friedl and Brodley 1997, Pal and Mather 2003) and use of parameters derived from forest structures such as vegetation age or biomass (Foody *et al.* 1996, Vieira *et al.* 2003,

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Lu 2005). However, the landscape complexity in colonization frontiers and the abundant tree species of the Amazonian forests often impair the separation of land-cover classes when using remotely sensed data, especially the distinctions between (1) successional vegetation stages and (2) successional vegetation and agroforestry.

Although several works have explored different approaches to classify successional vegetation stages (Mausel *et al.* 1993, Moran *et al.* 1994, Brondízio *et al.* 1996, Foody *et al.* 1996, Steininger 1996, Rignot *et al.* 1997, Yanasse *et al.* 1997, Lucas *et al.* 2002, Lu *et al.* 2003a, Vieira *et al.* 2003, Lu 2005), the accuracy achieved is still poor. The main difficulties stem from the continuous transition of successional vegetation stages and the similar stand structures between successional stages and agroforestry, or between the initial successional stage and degraded pasture. To date, remote-sensing approaches to effectively separate these classes have not been developed. Because of the recognized importance of successional vegetation and agroforestry systems in providing environmental services such as carbon sequestration and restoration of degraded lands, more accurate classifications will reduce uncertainties in models and evaluations using such information.

Most previous research uses single-sensor data only for land-cover classification, but rarely has research explored the integration of different sensor data to improve classification accuracy in the moist tropical regions. The different characteristics of optical and radar data may provide new insights for such a task. We assume that (1) incorporation of different spatial and spectral resolution data (e.g. Landsat Enhanced Thematic Mapper Plus (ETM+) multispectral and panchromatic data, Radarsat data), (2) combination of spectral signatures and textures and (3) combination of data fusion and textures may improve the results. Hence, this paper aims to identify a suitable image processing procedure for improving land-cover classification accuracy through a comparative analysis of different image combinations based on Landsat ETM+ and Radarsat data.

2. Study area

The state of Rondônia has experienced high deforestation rates since the 1970s (INPE 2002). Following the national strategy of regional occupation and development, colonization projects initiated by the Brazilian government played a major role in this process (Batistella *et al.* 2003). Most colonization projects in the state were designed to settle landless migrants. The immigrants have transformed the forested landscape into a mosaic of cultivated crops, pastures, and different stages of secondary succession and forest remnants. The study area is located at Machadinho d'Oeste in northeastern Rondônia. Settlement began in the mid-1980s, and since then land-use/cover trajectories following deforestation have put in place a dynamic process of forest fragmentation. A well-defined dry season lasts from June to August, the annual average precipitation is 2016 mm, and the annual average temperature is 25.5°C (Rondônia 1998). Batistella (2001) describes in detail the characteristics of this location, a landscape in transition from a matrix dominated by forest to land covers with lower carbon content.

3. Method

3.1 *Land-cover classification scheme*

A suitable classification scheme is critical for land-cover classification using remotely sensed data and for field data collection. Based on our previous experience in the region (e.g. Mausel *et al.* 1993, Brondízio *et al.* 1996, Lu *et al.* 2004), the requirement of subclasses of secondary succession for Amazonian research, and the importance of coffee plantations in this study area (Batistella and Moran 2005), we defined 12 classes to be mapped. Our previous research has indicated that three stages—initial (SS1), intermediate (SS2), and advanced (SS3) secondary succession—are suitable for most study areas (Brondízio *et al.* 1996, Lu *et al.* 2003a). Successional vegetation is assigned solely to areas where the grass cover is less than 25%, which generally occurs in sites that have been abandoned for more than two years. The separation of different successional stages is based on the vegetation stand structures, that is, average diameter at breast height (DBH), canopy height, and biomass (Lu *et al.* 2003a). The primary forest is separated into upland forest (UPF) and lowland forest (LLF) based on moist conditions and topographic factors.

In the initial few years after deforestation, the land is often used for annual crops and cattle ranching. Pasture lands are classified as cultivated pasture (CUP) and degraded pasture (DGP) based on land management and land cover. That is, cultivated pastures are defined as areas with grass cover greater than 75%, and degraded pastures are defined as areas with grass cover between 25% and 75%. Agroforestry (AGF) systems in the study area are productive arrangements that include economic tree species, coffee, cocoa and other understory species. Coffee plantations (CFP) are separated. Other land-cover classes include infrastructure (urban areas and roads), water and non-vegetation lowland (NVL).

3.2 *Field data collection*

Fieldwork was conducted during the dry seasons of 1999, 2000, 2002 and 2003. Vegetation surveys were conducted in areas with relatively homogeneous ecological conditions (i.e. topography, distance from water and land use). After defining the area to be surveyed (plot sample), three subplots including nested parcels of 1 m^2, 9 m^2 and 100 m^2 (small, medium, large, respectively) were randomly selected to accurately represent the variability within the plot sample. 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 DBH greater than 2 cm and smaller than 10 cm. Trees were defined as woody plants with a DBH greater than or equal to 10 cm. Total tree height, stem height (the height of the first main branch) and DBH were measured for all trees in the large parcels. Height and DBH were measured for all saplings in the medium parcels. Ground-cover estimation and counting of individuals were carried out for seedlings and herbaceous vegetation in the small parcels. In total, 26 plots of secondary succession and 14 plots of mature forest were sampled. The measured parameters were used for separation of different successional vegetation stages and primary forest classes based on canonical discriminant analyses (Lu *et al.* 2003a).

During fieldwork in August 2002, an IKONOS colour composite (acquired 28 May 2001) was used to support the observation of different successional vegetation stages, coffee plantations, and degraded and cultivated pastures. In August 2003, a Satellite pour l'Observation de la Terre (SPOT) colour composite was used to assist the collection of hundreds of observations over a larger area of approximately 2000 km^2. After driving extensively throughout the settlement, field observations provided familiarity with the structure of regrowth stages. Visual estimations of vegetation structure attributes, such as canopy height, allowed the rapid determination of the three secondary succession classes defined. The distinction of mature forest classes was based on topographic and moist conditions. Exploratory analysis of remote-sensing imagery and a digital elevation model built from topographic maps in 1 : 100, 000 scale supported the delimitation of such classes in the field. The separation of cultivated and degraded pasture classes was based on grass cover and condition. Every observation and sample plot was registered with a global positioning system (GPS) device to allow further integration with spatial data in geographic information systems (GIS) and image processing systems. The successional vegetation stages, coffee plantations, agroforestry systems, and pastures are mainly located near roads. The collection of georeferenced observations for these classes could be accurately located. Some primary forest sites were identified by visual interpretation of the IKONOS or SPOT colour composites and confirmed by local experts. The collected observations were separated into two groups: one group was used as training samples during the maximum-likelihood classification approach, and another group was used for assessing classification results. The difference between the image acquisition data (i.e. Landsat ETM+ and Radarsat data were acquired in 2001) and field data collection dates (i.e. in 2002 and 2003) were considered when determining vegetation classes, especially different successional stages, agroforestry systems, and pastures, based on land-use history and image interpretation. All sample plots were examined against the Landsat ETM+ image to make sure the land-cover classes were correctly assigned.

3.3 *Data preprocessing*

3.3.1 Landsat ETM+ data. Landsat 7 ETM+ data, which were acquired on 11 August 2001, were first geometrically registered to another Landsat TM image (18 June 1998), which was already rectified (Universal Transverse Mercator, south 20 zone). A nearest-neighbour algorithm was used to resample the Landsat ETM+ multispectral image into a pixel size of 30 m × 30 m and panchromatic image into 15 m × 15 m during image registration. A root-mean-square error of 0.36 pixels for the registration was obtained. An image-based dark object subtraction model was used to implement radiometric and atmospheric correction (Lu *et al.* 2002). The surface reflectance values after calibration ranged between 0 and 1. For the convenience of data analysis, the reflectance values were linearly rescaled to 8-bit integer format (0–255).

3.3.2 Radarsat data. The Radarsat C-band, HH polarization data, which were acquired on 21 September 2001, were used in this research. This image was converted to a backscattering coefficient (σ) using the following model (Ribbes and le Toan 1999, Chakraborty and Panigrahy 2000):

$$\sigma_j^0 = 10\log_{10}\left[\left(DN_j^2 + \alpha\right) \Big/ A_j\right] + 10\log_{10}[\sin(I_j)] \qquad (1)$$

where DN_j is the digital number (amplitude of the backscattered signal), A_j is the calibration coefficient (scaling gain value) of the jth pixel, α is a constant offset, and I_j is the incidence angle at the jth range pixel. The backscattered coefficient was then linearly rescaled to 8-bit integer format (0–255).

The Radarsat data were geometrically registered to 2001 Landsat ETM+ data with a root-mean-square error of 0.79 pixels. The image was resampled to a pixel size of 15 m × 15 m using a nearest-neighbour resampling algorithm. Reducing speckle in the Radarsat image was needed before it could be used for land-cover classification. Different filtering approaches have been examined in previous works, such as the enhanced Lee filter, the Lee-Sigma, and the Gamma MAP (Panigrahy *et al.* 1999, Rio and Lozano-Garcia 2000, Ndi Nyoungui *et al.* 2002). Here, the enhanced Lee filter was used.

3.4 *Data fusion*

Many methods have been developed to integrate spectral and spatial information. Pohl and Van Genderen (1998) reviewed methods for multisensor data fusion. The intensity-hue-saturation (IHS) transformation is the most frequently used method for improving the visual display of multisensor data (Welch and Ehlers 1987), but this approach can employ only three bands, and the resultant image may be unsuitable for classification. To preserve the spectral integrity of the input dataset, principal component analysis (PCA) is often used for data fusion to produce an output result for further quantitative analysis. Recently, wavelet-merging techniques have emerged as another effective approach to integrate spectral and spatial information contents (Li *et al.* 2002, Ulfarsson *et al.* 2003). Therefore, this paper used the wavelet-merging approach to integrate Landsat ETM+ multispectral and panchromatic or Radarsat data.

Wavelet theory is similar to the Fourier transform analysis, but the wavelet transform uses short, discrete wavelets, instead of a long wave as in the Fourier transform. One key step during the wavelet transform is to select the mother wavelet. The input image is broken down into successively smaller multiples of the mother wavelet. The derived wavelets have many mathematically useful characteristics that make them preferable to simple sine or cosine functions. Once the mother wavelet is defined, a family of multiples can be created with incrementally increasing frequency. Then the image can be decomposed by applying coefficients to each waveform. In theory, an image can be decomposed into high-frequency and low-frequency components. The wavelet family can be regarded as a high-pass filter. The low-frequency image is the lower spatial resolution image and the high-frequency image is the higher spatial resolution image containing the details of the image. In general, the high spatial resolution image is a single band, such as the Landsat ETM+ panchromatic band, so the substitution image from the multispectral image must also be a single band. Thus, PCA is used to convert the multispectral bands into new components. The first component contains most of the information and is used as the substitution image. A detailed description of the wavelet-merging technique is found in Lemeshewsky (1999) and ERDAS Field Guide (2003). In this research, the higher spatial resolution data—Landsat ETM+ panchromatic and Radarsat data—were used to integrate the Landsat ETM+ multispectral data with the wavelet-merging technique in order to incorporate the high spatial resolution information and to preserve the Landsat ETM+ multispectral features in the new, fused image.

3.5 *Texture analysis*

Textures have proven useful in improving land-cover classification accuracy. Many texture measures have been developed (Haralick *et al.* 1973, Kashyap *et al.* 1982, Emerson *et al.* 1999), and used at this scope (Marceau *et al.* 1990, Augusteijn *et al.* 1995, Groom *et al.* 1996, Shaban and Dikshit 2001, Chen *et al.* 2004). Many previous applications of textures are related to urban studies because of the complexity of urban landscapes requiring higher spatial resolution data such as SPOT HRV. For Amazonian land-cover classification, the role of textures has not been extensively explored. The enhanced characteristics of Landsat ETM+ data include a panchromatic band of 15-m spatial resolution, which provides richer textural and contextual information than multispectral bands with 30-m spatial resolution. Use of textures based on the Landsat ETM+ panchromatic band may improve classification accuracy. Also, radar data are often used in texture form. Hence, in our study, texture analysis focused on Landsat ETM+ panchromatic and Radarsat data.

The GLCM-based (grey level co-occurrence matrix) texture measures are often used. In this paper, eight GLCM-based texture measures (i.e. mean [ME], variance [VA], homogeneity [HO], contrast [CO], dissimilarity [DI], entropy [EN], second moment [SM] and correlation [CC]) associated with three window sizes (9×9, 15×15, and 21×21) were explored. The texture images were rescaled to 8-bit integer format (0–255). The Jeffries-Matusita (J-M) algorithm was used to analyse the separability of land-cover classes based on training sample plots (Mausel *et al.* 1993, Landgrebe 2003). Pearson's correlation analysis was used to analyse the correlation between the selected textures. The textures with high separability but low correlation coefficients were selected based on the following equation:

$$\text{Best texture combination (BTC)} = \sum_{i=1}^{n} \mathrm{JM}_i \Bigg/ \sum_{j=1}^{n} R_{ij} \qquad (2)$$

where JM is the Jeffries-Matusita distance value based on the training sample plots, R_{ij} is the correlation coefficient between image i and j, and n is the number of textural images.

3.6 *Comparative analysis of different image combinations*

Many potential image processing procedures can be used for land-cover classification. Hence, identification of the most suitable procedure to improve classification accuracy has considerable significance. In practice, it is not straightforward to define a suitable procedure for a specific study area. In this paper, we present a comparative analysis of different combinations of spectral features and textures based on Landsat ETM+ spectral signatures, GLCM-based textures with Landsat ETM+ panchromatic or Radarsat data, data fusion from Landsat ETM+ multispectral and panchromatic or Radarsat data. Table 1 summarizes the different image combinations used in this research. All images were rescaled to 8-bit integer format (0–255) before being used for image classification.

Training sample plots were examined on the 2001 Landsat ETM+ image. Approximately 12–20 sample plots were selected for each class with a polygon size of 9 to 40 pixels for each plot, depending on the homogeneity of the land-cover patch. The maximum-likelihood classifier (MLC) was used to classify the images with the same training sample plots. A majority filter with a window size of 3×3 pixels was used to remove the 'salt and pepper' effect in the classified images.

The comparative study of different image combinations is based on the accuracy assessment of the land-cover classification images. A common method for accuracy assessment is through the use of an error matrix. Literature on this methodology describes the meanings of and calculations for overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA) and Kappa coefficient (KA) (Congalton 1991,

Table 1. Design of image processing routines.

Sensor data	Code	Description
ETM	ETM-ALL	Six ETM+ reflective bands with 30-m spatial resolution
	ETM-Pan	A combination of six ETM+ reflective bands and one ETM+ panchromatic band
	ETM-Pantxt	A combination of ETM-ALL and three textures from ETM+ panchromatic band
	ETM-Radartxt	A combination of ETM-ALL and three textures from Radarsat C-HH band
ETM-Pan-fusion	Pan-fusion	Data fusion based on six reflective ETM+ bands and one ETM+ panchromatic band
	Pan-fusion-Pantxt	A combination of Pan-fusion and three textures from one ETM+ panchromatic band
	Pan-fusion-Radartxt	A combination of Pan-fusion and three textures from Radarsat C-HH band
	Pan_fusion_PanRadartxt	A combination of Pan-fusion and three textures from ETM+ panchromatic band and three textures from Radarsat C-HH band
ETM-Radar-fusion	Radar-fusion	Data fusion based on six ETM+ reflective bands and one Radarsat C-HH band
	Radar-fusion-Radartxt	A combination of Radar-fusion and three textures from Radarsat C-HH band
	Radar-fusion-Pantxt	A combination of Radar-fusion and three textures from ETM+ panchromatic band
	Radar-fusion-PanRadartxt	A combination of Radar-fusion and three textures from ETM+ panchromatic band and three textures from Radarsat C-HH band

Smits *et al.* 1999, Foody 2002). In this paper, test sample plots have been selected using the fieldwork carried out in 2002 and 2003 and visual interpretation of the IKONOS image. A total of 345 sample plots were used for accuracy assessment. An error matrix for each classification image was produced and UA, PA, OA and KA were calculated.

4. Results

4.1 *Selection of textures for classification*

Separability analysis reveals the capability of single textures to distinguish land-cover classes, and the BTC approach helps to identify the potentially best combination of textures for land-cover classification. The textures with separability values greater than 500 for the Landsat ETM+ panchromatic band and greater than 300 for the Radarsat image were selected (table 2). The correlation coefficients of the selected textures indicate that some textures are highly correlated. For example, the

Table 2. Comparison of separability among the textures based on the Jeffries-Matusita distance algorithm.

Sensor data	Window size (m)	Separability based on single texture							
		ME	VA	HO	CO	DI	EN	SM	CC
Landsat ETM+ panchromatic band	9×9	1056	350	398	372	381	459	486	406
	15×15	1032	515	480	478	487	481	551	488
	21×21	984	562	509	497	524	507	578	503
Radarsat	9×9	708	285	188	319	228	161	135	284
	15×15	782	359	269	347	286	277	249	335
	21×21	812	460	298	377	317	324	276	401

ME, mean; VA, variance; HO, homogeneity; CO, contrast; DI, dissimilarity; EN, entropy; SM, second moment; CC, correlation.

correlation coefficients are 0.96, −0.92 and −0.90, respectively, between textural images based on contrast (CO) and dissimilarity (DI), homogeneity (HO) and DI, and entropy (EN) and second moment (SM) from the Landsat ETM+ panchromatic band. The textural images with high correlation coefficients have similar information contents. Therefore, the selection of textures with high separability values but low correlation coefficients between them is important. The analysis of best texture combinations (BTC) indicates that the best three textures are mean (ME) with a 15×15 window and variance (VA) and SM with a 21×21 window based on panchromatic band, and ME, VA and CO with a 21×21 window based on the Radarsat C-HH band. These textures were combined with Landsat ETM+ spectral images for classification.

4.2 *Comparison of classification accuracies*

This research indicates the difficulty of using remotely sensed data for land-cover (especially vegetation) classification in moist tropical regions. Table 3 summarizes the classification accuracies of different image combinations. Overall, non-vegetation classes (i.e. infrastructure [INF], water [WAT] and non-vegetation lowland [NVL]) have higher classification accuracies than vegetation classes (e.g. primary forest, secondary succession, pastures), and primary forest (e.g. upland forest [UPF] and lowland forest [LLF]) has higher accuracy than different secondary successional stages. The classification accuracies of intermediate and advanced successions (SS2 and SS3), agroforestry (AGF) and degraded pasture (DGP) are especially poor because of the similar spectral features between SS2, SS3 and AGF and between DGP and initial succession (SS1). The six Landsat ETM+ spectral bands (ETM-ALL) and the combination of six spectral bands and one panchromatic band (ETM-Pan) produced similar classification accuracies, except for SS2, which slightly improved accuracy, and AGF, which slightly decreased accuracy in ETM-Pan. The combination of textures from the panchromatic band (ETM-Pantxt) slightly improved classification accuracy compared to ETM-ALL, but the overall classification accuracy from the combination of textures from Radarsat data (ETM-Radartxt) slightly decreased. The overall classification accuracy from the data fusion images (based on either Landsat ETM+ multispectral and panchromatic data (Pan-fusion) or Landsat ETM+ multispectral and Radarsat data [Radar-fusion]) slightly decreased compared to the original ETM-ALL data. However, the incorporation of data fusion with textures from higher spatial resolution

Table 3. A comparison of different combinations of Landsat ETM+ spectral features and textures.

	ETM-ALL		ETM-Pan		ETM-Pantxt		ETM-Radartxt	
Type	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%
UPF	73.08	95.00	73.08	90.48	80.77	91.30	73.08	86.36
LLF	84.62	64.71	84.62	64.71	92.31	75.00	84.62	64.71
SS3	46.15	18.18	46.15	18.75	84.62	27.50	46.15	18.75
SS2	21.43	45.00	23.81	47.62	21.43	52.94	14.29	35.29
SS1	64.62	63.64	64.62	63.64	61.54	63.49	61.54	59.70
DGP	48.65	66.67	45.95	65.38	48.65	58.06	48.65	54.55
CUP	90.91	94.34	90.91	94.34	96.36	94.64	89.09	92.45
AGF	62.50	37.04	59.38	35.85	46.88	40.54	59.38	42.22
CFP	66.10	73.58	67.8	74.07	72.88	71.67	67.80	71.43
INF	90.91	100.00	90.91	100	90.91	100.00	90.91	90.91
WAT	100.00	84.62	100	84.62	100.00	78.57	100.00	78.57
NVL	83.33	100.00	83.33	100	75.00	100.00	75.00	100.00
OA	65.16		65.16		67.02		63.30	
KA	0.6089		0.6087		0.6297		0.5877	

	Pan-fusion		Pan-fusion-Pantxt		Pan-fusion-Radartxt		Pan-fusion-PanRadartxt	
Type	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%
UPF	76.92	90.91	80.77	87.50	84.62	84.62	80.77	95.45
LLF	84.62	61.11	92.31	66.67	84.62	68.75	100.00	72.22
SS3	69.23	22.50	84.62	32.35	46.15	23.08	69.23	40.91
SS2	21.43	36.00	23.81	52.63	19.05	53.33	16.67	70.00
SS1	53.85	61.40	63.08	62.12	70.77	62.16	81.54	59.55
DGP	40.54	53.57	45.95	58.62	45.95	54.84	40.54	60.00
CUP	89.09	94.23	96.36	94.64	92.73	92.73	98.18	91.53
AGF	53.13	34.00	43.75	34.15	50.00	42.11	43.75	58.33
CFP	57.63	68.00	66.10	69.64	74.58	70.97	86.44	68.92
INF	90.91	90.91	90.91	100.00	90.91	100.00	90.91	100.00
WAT	100.00	78.57	100.00	78.57	100.00	73.33	100.00	78.57
NVL	75.00	100.00	75.00	100.00	66.67	100.00	75.00	100.00
OA	60.90		65.96		66.49		71.01	
KA	0.5629		0.6176		0.6219		0.6706	

images—Landsat ETM+ panchromatic or Radarsat data—is helpful in improving classification accuracies. In particular, the combination of data fusion and textures from both panchromatic and Radarsat data improved overall accuracies by 5.8% to 6.9% if compared to ETM-ALL.

5. Discussion and conclusion

Vegetation classification in the moist tropical region, especially of land-cover types like SS2 and SS3, is very difficult, but the use of textures is an effective approach for improvement. Indeed, a combination of textures and image data fusion generally improved classification accuracy by approximately 5.8–6.9% when compared to using the original Landsat ETM+ spectral images. On the contrary, the data fusion based on Landsat ETM+ multispectral and panchromatic data or Radarsat data did not effectively improve classification accuracies.

Table 3. (*Continued.*)

	Radar-fusion		Radar-fusion-Radartxt		Radar-fusion-Pantxt		Radar-fusion-PanRadartxt	
Type	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%
UPF	84.62	95.65	84.62	88.00	80.77	95.45	80.77	95.45
LLF	92.31	80.00	84.62	68.75	92.31	70.59	100.00	72.22
SS3	76.92	25.64	61.54	26.67	84.62	31.43	61.54	44.44
SS2	26.19	47.83	16.67	43.75	21.43	52.94	16.67	63.64
SS1	55.38	61.02	69.23	62.50	63.08	60.29	89.23	63.04
DGP	45.95	58.62	43.24	50.00	43.24	64.00	37.84	58.33
CUP	90.91	96.15	90.91	92.59	98.18	94.74	98.18	91.53
AGF	56.25	36.00	56.25	51.43	50.00	38.10	46.88	55.56
CFP	62.71	71.15	77.97	73.02	69.49	68.33	86.44	70.83
INF	90.91	90.91	90.91	100.00	90.91	100.00	90.91	100.00
WAT	100.00	78.57	100.00	73.33	100.00	78.57	100.00	78.57
NVL	75.00	100.00	66.67	100.00	75.00	100.00	75.00	100.00
OA	64.63		67.02		66.76		72.07	
KA	0.6040		0.6282		0.6260		0.6823	

PA, producer's accuracy; UA, user's accuracy; OA, overall accuracy; KA, kappa coefficient. UPF, upland forest; LLF, lowland forest; SS3, advanced successional vegetation; SS2, intermediate successional vegetation; SS1, initial successional vegetation; DGP, degraded pasture; CUP, cultivated pasture; AGF, agroforestry; CFP, coffee plantation; INF, infrastructure; WAT, water; NVL, non-vegetation lowland.

The complex forest stand structures and abundant tree species may be the most important factors inducing difficulty of vegetation classification in the Amazon. For example, the smooth transition between stages of successional vegetations and the spectral confusion between successional vegetations and agroforestry makes their classification accuracies poor. Agroforestry is a complex category, including a variety of productive arrangements based on the association of two or more species. Another problem is the difficulty in collecting sufficient training and test samples for some vegetation classes, especially for successional stages. In this study area, the lack of typical SS3 samples is an important factor resulting in poor SS3 classification accuracy. The selected SS3 samples are mainly in younger stages of SS3 and are often confused with old SS2 vegetation because of their similar vegetation stand structure.

This research has shown that texture measures represent an important factor in improving land-cover classification accuracies. One critical step is to identify suitable textures that provide the best separability for the land-cover classes. However, selection of suitable textures is a challenge because textures vary with the characteristics of the landscape under investigation and images used. Identifying suitable textures involves the selection of appropriate texture measures, moving window sizes, and image bands (Franklin *et al.* 1996, Chen *et al.* 2004). Not all texture measures can improve classification performance. Even for the same texture measure, selecting the appropriate window size and spectral band is crucial. The BTC approach provides an easy way to identify the best combination of textures to improve classification performance based on the separability of land-cover classes and correlation coefficients between the selected textures.

The data fusion image enhanced visual interpretation through the incorporation of high spatial resolution information in the fused dataset. However, data fusion may decrease classification accuracy, especially for the vegetation types with lack of obvious stand structures, such as SS1 and DGP in this study. The major reason may be that data fusion increases the variation within the same vegetation class. On the contrary, textures make use of the spatial information inherent in the image and reduce the spectral variation. Thus, use of data fusion and texture benefits the land-cover classification.

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