A Comparative Study of Terra ASTER, Landsat TM, and SPOT HRG data For Land Cover Classification in the Brazilian Amazon

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Abstract: Landsat Thematic Mapper (TM) data have been extensively used for land cover classification, but Terra ASTER and SPOT High Resolution Geometric (HRG) data applications are just beginning. This paper compares the capabilities of TM, ASTER, and HRG in land cover classification in the Amazon basin. Maximum likelihood classification was used for selected multi-sensor image classification. This research indicates that different sensor data have their own merits for land cover classification and no single sensor data or image processing routine provide the best classification accuracy for all land cover classes. The SPOT data fusion result with its 5 m spatial resolution provides the best overall classification accuracies, with Kappa coefficients of 61.8% and 56.3% for 13 land cover classes and 9 vegetation classes, respectively. This is about 3% higher than the second best classification results using SPOT multispectral data with 10 m spatial resolution and ASTER data; and about 4% higher than TM data for 9 vegetation classes. The major errors are due to the confusion between successional stages, agroforestry, and degraded pasture. For the six land cover classification system, the SPOT data fusion provides the best classification accuracy, with overall classification accuracy of 80.4% and kappa coefficient of 75.4%. This research indicates the importance of short-wave infrared bands in land cover classification. Also, higher spatial resolution images provide better classification accuracy when the spectral wavelengths are similar.

Keywords: land cover, classification, ASTER, TM, SPOT HRG, maximum likelihood classification, Amazon

1. INTRODUCTION

The Brazilian Amazon basin has experienced high deforestation rates since the 1970s (INPE, 2002). Deforestation has converted a vast area of primary forest into a mosaic of different stages of successional forests, agroforestry, crops, and pasture. It is estimated that about 20-50% of the deforested areas are in certain stage of secondary succession (Moran et al., 1994; Skole et al., 1994; Lucas et al., 2000; Roberts et al., 2002). The rapid regrowth and increasing areal extent of successional forests play an important role in regional and global carbon budget. Also, they have significant ecological functions within Amazonian ecosystems and landscapes, such as increasing soil fertility, changing vegetation structure and composition, and promoting faunal dispersion (Moran et al., 2000). Accurate classification of successional stages and distinction of successional forests from agroforestry and degraded pastures become considerably important in reducing the uncertainty in estimations of carbon emission and sequestration besides providing elements for the evaluation of land degradation or restoration. However, the complexity of vegetation stand structure, the smooth transition between adjacent successional stages, abundant tree species, and heterogeneous environmental conditions often create difficulties in Amazonian vegetation classification. Many previous initiatives only classified the moist tropical forest into two broad categories – successional forest and primary forest (Adams et al., 1995; Roberts et al., 1998; 2002, Powell et al., 2004). However, biomass of different successional stages ranges from less than 2 kg/m^2 in initial succession stages to more than 20 kg/m^2 in advanced succession stages. Obviously, their roles in restoring degraded lands and in carbon sequestration vary significantly. Moreover, biomass of primary forests ranges from approximate 12 kg/m^2 to greater than 50 kg/m^2 due to different soil conditions, topography, and nutrient availability (Lu et al., 2005). A single class of primary or secondary forest is obviously not sufficient for many applications such as carbon cycling study. So, a careful delineation of vegetation classes is required.

Landsat TM/ETM+ data are often used for land cover classification (Adams et al., 1995; Roberts et al., 1998; Lu et al., 2004). As higher spatial and/or spectral resolution satellite data are readily available, identification of suitable sensor data for land cover classification in the moist tropical regions is key for providing better classification results. For example, ASTER data with improved spatial and spectral resolutions and SPOT HRG data with high spatial resolution may provide better land cover classification performance than Landsat TM data. Although TM data have been extensively used for land cover classification in the Amazon basin, ASTER and HRG data applications are just beginning. Their capabilities for land cover, especially vegetation, classification are poorly understood. Hence, this paper aims to compare the performance of Terra ASTER, Landsat TM, and SPOT HRG data in land cover, especially vegetation classification and to explore the suitable image processing routine for vegetation classification in the Amazon.

2. STUDY AREA

The study area is located in northeastern Rondônia, Brazil. Settlements were implemented in the early-1980s in this location. Very limited deforestation occurred before 1988 as found on the 1988 TM image. However, deforestation has rapidly increased in the 1990s and has converted a vast area of primary forest into coffee plantation, pasture, and successional forests (Batistella et al., 2003). The majority of successional forests in this study area are less than 15 years old. Several soil types, mainly alfisols, oxisols, ultisols, and alluvial soils, were identified (Bognola and Soares, 1999). The terrain is undulating, ranging from 100 m to 450 m above sea level. The well-defined dry season lasts from June to August. The annual average precipitation is 2,016 mm, and the annual average temperature is 25.5°C (Rondônia, 1998).

3. METHODS

3.1 Field data collection and the land cover classification system

A suitable classification system is critical for land cover classification using remotely sensed data and for field data collection. The selection of the land-cover classification scheme was motivated by three factors: (1) our previous experience in land-cover classification in the Amazon basin during the past decade, (2) the requirement of subclasses of secondary succession for Amazonian research, and (3) the requirement for discrimination of successional forests from pasture and agroforestry. Therefore, two land cover classification systems, with six classes for level I and 13 classes for level II were designed (Table 1). In this research, the emphasis was on vegetation classification. The primary forest was separated into upland dense forest, upland open forest, and lowland forest based on biomass and soil moist conditions. The successional forests were classified as initial (SS1), intermediate (SS2), and advanced (SS3) secondary succession based on vegetation stand structures. Pasture land was classified as cultivated and degraded pastures based on the pasture condition. Agricultural lands include agroforestry (such as coffee plantations and mixture of coffee and other tree species) and recently deforested areas. A detailed description about these vegetation classes, especially the different successional forest stages, is found in Lu et al. (2003).

Table 1. Land-use and land-cover classification system

Level I	C I	Level II	C II
Primary forest	PF	Upland dense forest Upland open forest Lowland forest	UDF UOF LLF
Secondary succession	SS	Advanced succession Intermediate succession Initial succession	SS3 SS2 SS1
Pasture	PA	Degraded pasture Cultivated pasture	DGP CUP
Agricultural land	AL	Agroforestry Bare soils (recently deforested area)	AGF BAS
Built-up land	BL	Built-up land	BUL
Water body	WB	Water Non-vegetated wetland	WAT NVW

Field data collection was conducted in August 2002 and 2003. During field work in August 2002, an IKONOS image was used to assist the selection of different successional forest stages, coffee plantation and other agroforestry, and degraded and cultivated pastures. In August 2003, a SPOT image was used to assist the selection of more land cover classes. After driving extensively throughout the settlements, field observations gave insights about the structure of regrowth stages, mainly regarding total height and ground cover of dominant species. The surveys were implemented in areas with relatively homogeneous ecological conditions (e.g., topography, distance from water, and land use) and uniform physiognomic characteristics. Every sample 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. The successional forest stages, agroforestry, and pastures are mainly located near the roads. The collection of sample plots for these classes is relatively easy and can be accurately located based on GPS points and IKONOS or SPOT images. However, the collection of primary forest data is often more difficult due to problems of access. Hence, most sample plots for the upland dense forest, upland open forest, lowland forest, and non-vegetated classes (e.g., road, urban, water, non-vegetated wetland, and recently deforested areas) were identified based on visual interpretation of IKONOS or SPOT color composites. The collected sample plots were separated into two groups. One group was used for training sample plots in the supervised classification and another group was used as test sample plots for accuracy assessment.

3.2 Image preprocessing

Three different sensor data, i.e., Terra ASTER, Landsat 5 TM, and SPOT 5 HRG, were used in this research. The 30 m spatial resolution TM image with four visible and near infrared (VNIR), and two short-wave infrared (SWIR) bands was acquired on July 8, 2003, with sun elevation angle of 42.966° and sun azimuth angle of 45.719°. The SPOT HRG image with one 5 m resolution panchromatic band, three 10 m resolution VNIR bands, and one 20 m resolution SWIR band was acquired on June 26, 2003, with sun elevation angle of 51.065° and sun azimuth angle of 31.848°. The ASTER image with three 15 m resolution VNIR bands, six 30 m resolution SWIR bands, and five 90 m resolution thermal infrared (TIR) bands was acquired in August 1, 2003, with sun elevation angle of 52.666° and sun azimuth angle of 42.766°. Thermal bands were not used in this research because of its coarse spatial resolution and thermal features.

Geometric correction and atmospheric calibration are two important aspects in the image preprocessing. Although data products are geometrically corrected when they are purchased, the geometric precision is not high enough for high-resolution multi-sensor data analysis. Therefore, accurate rectification or registration based on control point data is often needed. The L1A SPOT data product was first checked with other ETM+ data, which were geometrically rectified already, and found to have high rectification accuracy. After checking the geometric accuracies of ASTER and TM data with the SPOT image, about two to four pixel errors were found, and thus accurate registration for these images was required. The SPOT image was used as the reference data. The TM and ASTER images were registered to the SPOT image with the Universal Transverse Mercator coordinate system. The nearest-neighbor algorithm was used to resample the registered images to suitable resolutions based on the selected sensor data. In the final results, the TM image was resampled to 30 m and the ASTER image to 15 m spatial resolution. Errors of 0.1816 pixels (x error: 0.1409, y error: 0.1145) for the L1G TM image and of 0.3219 pixels (x error: 0.2116, y error: 0.2426) for the L1B ASTER image were obtained during image registration.

The L1B ASTER data product was directly imported into radiance value and then rescaled to 8 bit integer format. No further atmospheric calibration was conducted for the ASTER data. The atmospheric calibration of TM and SPOT images was conducted using an improved DOS model (dark-object subtraction). This approach is an image-based procedure that corrects for the effects caused by sun zenith angle, solar radiance and atmospheric scattering (Chavez, 1996; Lu et al., 2002).

$$R_\lambda = PI * D*(L_\lambda - L_{\lambda.haze})/(Esun_\lambda * COS(\theta)),$$

$$L_\lambda = DN_\lambda/A_\lambda \text{ , for SPOT data, and}$$

$$L_\lambda = gain_\lambda * DN_\lambda + bias_\lambda \text{ , for TM data,}$$

Where L_λ is the apparent at-satellite radiance for spectral band λ, DN_λ is the digital number of selected band λ, A_λ is the calibration factor for spectral band λ of SPOT image, R_λ is the calibrated reflectance, $L_{\lambda.haze}$ is path radiance, Esun $_\lambda$ is exo-atmospheric solar irradiance, D is the distance between the Earth and Sun, and θ is the sun zenith angle. The path radiance for each band was identified based on analysis of water bodies and shades in the images. The calibrated TM and SPOT images were also rescaled to 8 bit integer format. After geometric and atmospheric correction of the selected sensor images, correlation analysis was used to explore the relationships between bands and principal component analysis (PCA) was used to explore data redundancy.

3.3 Supervised classification

In order to explore land cover classification performance among the three sensor data, different image processing routines were designed (Table 2). These image processing routines explore how different spatial and spectral resolutions influence land cover, especially vegetation, in terms of classification accuracies, and compare how different sensor data with different spatial resolutions influence the vegetation classification accuracies. The spatial resolutions range from 5 m (SPOT data fusion result), 10 m (SPOT multispectral image), 15 m (ASTER data), and 30 m (TM data). The spectral bands used range from 4 (SPOT data) to 7 (TM data), and to 9 (ASTER data). In order to make full use of high spatial resolution SPOT panchromatic image, the wavelet-merging technique was used to integrate SPOT multispectral bands and panchromatic band.

Table 2. Summary of different image processing routines

Sensor	Treatments	Code	Res.	Bands
ASTER	VNIR data	AST123	15 m	3
	VNIR and SWIR1	AST1234	15	4
	VNIR and SWIR1, 2	AST12345	15	5
	VNIR and all SWIR bands	AST-ALL	15	9
TM	TM all bands	TM-ALL	30	6
	TM bands 2, 3, 4, and 5	TM2345	30	4
SPOT	SPOT bands 1, 2, 3, and 4	SPOT1234	10	4
	Data fusion	SPOT-Fusion	5	4

Note: VNIR and SWIR represent visible and near infrared bands and shortwave infrared bands. Res. means spatial resolution of the sensor data. Data fusion is based on the SPOT multispectral bands and panchromatic band using the wavelet-merging technique.

The maximum likelihood classifier (MLC) was used to classify the spectral images for every processing routine. The training sample plots were selected based on field data collected in 2002 and 2003. For the level II classification system, 12 – 20 samples plots were selected for each class. A polygon of 9 to 40 pixels for each plot was selected, depending on the homogeneity of the land cover type. After selection of training samples, spectral separability was analyzed, and then the refined training samples were used to implement supervised classification using the MLC. The same training sample plots were used to implement image classification for each image processing routine using the MLC. The LULC classification results based on the level II system were first conducted, then the level I results were generated through reclassification according to the hierarchical scheme listed in Table 1.

3.4 Accuracy assessment

The error matrix is the most common approach for assessing land cover classification accuracy. Based on the error matrix, overall accuracy, producer's accuracy, user's accuracy, and Kappa coefficient can be calculated. Previous literature has provided the meanings and calculation methods for these parameters (Congalton *et al.*, 1983; Congalton, 1991; Smits *et al.*, 1999, Foody 2002); therefore, they are not discussed with details here. Because of the difficulty and time allocation in collecting training samples for land cover classes in moist tropical forest regions, the selection of a sufficient number of test sample plots based on randomly sampling is extremely difficulty. In this paper, a total of 365 sample plots were used for accuracy assessment, which were mainly collected during field work in 2002 and 2003, especially for different successional forest stage, agroforestry, degraded and cultivated pastures because they are difficult to visually discriminate on the images. Some land-cover classes, such as built-up land and dense forest, which can be easily identified on the images, were selected from the SPOT or IKONOS color composite. Accuracy assessments based on both classification systems were conducted. The producer's accuracy and user's accuracy for each class, as well as the overall accuracy and the kappa coefficient for each image processing routine were summarized to compare and analyze the performances of different spatial and/or spectral resolutions in land cover classification in the Amazon.

4. RESULTS AND DISCUSSION

4.1 Comparison of basic features among the three sensor data

Table 3 summarizes the correlation analysis results for the three sensor data. There are some common features, such as (1) the NIR band has low correlation with all other bands, indicating its independence in information and its importance; (2) the correlations between visible bands or between SWIR bands are strong, indicating high data redundancy. For example, the ASTER NIR band is negatively correlated with all other bands with correlation coefficients ranging from -0.12 to -0.08; the TM NIR band is positively correlated with other bands with correlation coefficients ranging from 0.08 to 0.34; and the SPOT NIR band is also positively correlated with other bands with correlation coefficients ranging from 0.18 to 0.41. Conversely, the correlation coefficients between SWIR bands are very strong. The correlation coefficients between ASTER SWIR bands are greater than 0.97 and between TM SWIR bands is 0.96. The high correlation coefficients imply similar information representing land cover surface characteristics. The PCA results listed in Table 4 confirm the high data redundancy inherent in the multispectral images. In ASTER data, although the SWIR bands increase to six comparing to two in TM and only one in SPOT, the very high correlations between the SWIR bands indicate that the increased information may be limited. The majority of information, accounting for 99% of the overall variance, is concentrated on the first three PCs based on PCA result of ASTER data. In the TM data, the first four PCs account for 99% and in SPOT, the first three PCs account for 99.6%. This indicates that the data redundancy is relatively small in SPOT, but it is high in the ASTER image.

Table 3. Correlation analysis results for the three sensor data

Sensor	Bands	Blue	Green	Red	NIR	SWIR1	SWIR2	SWIR3	SWIR4	SWIR5	SWIR6
ASTER	Green		1.000	**0.978**	-0.090	**0.909**	**0.917**	**0.916**	**0.918**	**0.916**	**0.901**
	Red		0.978	1.000	-0.177	**0.921**	**0.928**	**0.933**	**0.933**	**0.933**	**0.910**
	NIR		-0.090	-0.177	1.000	-0.083	-0.160	-0.167	-0.168	-0.183	-0.166
	SWIR1		0.909	0.921	-0.083	1.000	**0.979**	**0.985**	**0.979**	**0.973**	**0.951**
	SWIR2		0.917	0.928	-0.160	0.979	1.000	**0.991**	**0.989**	**0.987**	**0.976**
	SWIR3		0.916	0.933	-0.167	0.985	0.991	1.000	**0.991**	**0.990**	**0.971**
	SWIR4		0.918	0.933	-0.168	0.979	0.989	0.991	1.000	**0.992**	**0.974**
	SWIR5		0.916	0.933	-0.183	0.973	0.987	0.990	0.992	1.000	**0.976**
	SWIR6		0.901	0.910	-0.166	0.951	0.976	0.971	0.974	0.976	1.000
TM	Blue	1.000	**0.893**	**0.895**	0.159	**0.841**	**0.852**				
	Green	0.893	1.000	**0.947**	0.235	**0.896**	**0.890**				
	Red	0.895	0.947	1.000	0.088	**0.899**	**0.930**				
	NIR	0.159	0.235	0.088	1.000	0.340	0.151				
	SWIR1	0.841	0.896	0.899	0.340	1.000	**0.961**				
	SWIR2	0.852	0.890	0.930	0.151	0.961	1.000				
SPOT	Green		1.000	**0.962**	0.350	**0.883**					
	Red		0.962	1.000	0.179	**0.870**					
	NIR		0.350	0.179	1.000	0.410					
	SWIR1		0.883	0.870	0.410	1.000					

Table 4. PCA analysis results among the three sensor data

PC	ASTER		TM		SPOT	
	%	Accu%	%	Accu%	%	Accu%
PC1	87.27	87.27	80.84	80.84	71.70	71.70
PC2	9.20	96.48	13.77	94.61	24.39	96.09
PC3	2.53	**99.00**	3.16	97.77	3.54	**99.63**
PC4	0.44	99.45	1.28	**99.05**	0.37	100.00
PC5	0.23	99.67	0.55	99.59		
PC6	0.12	99.79	0.41	100.00		
PC7	0.09	99.88				
PC8	0.07	99.94				
PC9	0.06	100.00				

Note: PC means principal component; % indicates the percentage of variance in certain PC accounting for the overall variance; Accu% means the accumulated percentage.

4.2 Comparison of classification results

Table 5 summarizes the accuracy assessment results for the different processing routines based on 13 land cover classes. Different treatments have their own merits in separating land cover classes and no single treatment can provide the best classification accuracy for all classes. For example, the TM2345 provides the best classification accuracy for UDF, DGP, CUP, and AGF; the SPOT data provide the best results for SS3 and SS1; and AST-ALL is better for UOF and LLF. Comparing the accuracies among the land cover classes, non-vegetated classes (i.e., bare soil, built-up land, water, and non-vegetated wetland) have higher classification accuracies than vegetation classes. Successional forest stages, especially SS2 and SS3, have poorer classification accuracies than any other vegetation classes. Overall, the SPOT-Fusion provides the best classification accuracy and kappa coefficient; the SPOT1234 and AST-ALL provide similar kappa coefficient for the 9 vegetation classes; and the AST123 provides the poorest accuracy, with a kappa coefficient of only 42.6% due to the lack of SWIR bands in this routine. The comparison between SPOT1234 and SPOT-Fusion routines indicates that increased spatial resolution through wavelet-merging techniques improved about 3% in the kappa coefficient. Most land cover classes, excluding SS2 and SS3, improved classification accuracies to a certain degree. Comparing TM2345 and TM-ALL, the TM2345 routine provides better classification accuracies for most land cover classes than TM-ALL, implying that addition of more spectral bands with high correlation coefficients between them may decrease the classification accuracy. Comparing the four routines based on ASTER data, AST123 provides the poorest classification results. The accuracy improves when adding more SWIR bands. This indicates the importance of SWIR bands in vegetation classification.

Table 5 shows that most land cover classification accuracies based on ASTER data are poorer than those based on TM or SPOT. Different reasons may cause this problem. For example, the different image acquisition dates may produce difficulties for the comparison of classification results. The SPOT and TM images were acquired in late June and early July, the beginning of dry season, while the ASTER image was acquired in early August, the late period of the dry season. The different moist conditions may change land cover reflectance and the separation of land cover classes. Comparison between the images indicates that moist features (e.g. non-vegetated wetland) are more conspicuous in SPOT or TM images than in the ASTER image. The relatively drier condition in the ASTER data causes severe confusions among some land cover classes, such as between bare soils and cultivated pastures, between degraded pastures and SS1, and between agroforestry, degraded pasture, and different SS stages. Because of the different moist conditions, some sample plots for the non-vegetated wetland identified in TM or SPOT became bare soil in the ASTER image. A similar situation is for lowland forest that appeared in TM or SPOT image but became upland dense or open forest in the ASTER image. Also, the different training and test sample plots between TM (or SPOT) and ASTER make the comparison difficult because the ASTER image covers a smaller study area than TM and SPOT image, thus many training and test samples are out of the ASTER image. The decreased number of training sample plots and test sample plots may affect the classification results and accuracy assessment for the ASTER image.

Table 5 indicates that the classification accuracies for SS2 and SS3 classes are especially poor compared with other land cover classes based on the selected three sensor data. For SS3, an important constraint is that no typical training or test sample plots were available because they are in a younger stage of SS3 and they have similar vegetation stand structure as older SS2. Also, small SS3 areas in the study area limit the selection of sufficient number of training and test sample plots. The confusion of SS2 with agroforestry and SS3 makes the SS2 classification poorer because the coffee plantation and mixtures of coffee and other trees have similar reflectance as SS2.

Table 5. Comparison of classification accuracies among different processing routines based on level II classification scheme

Class	SPOT HRG				Landsat TM				Terra ASTER							
	SPOT1234		SPOT-Fusion		TM2345		TM-ALL		AST-ALL		AST123		AST1234		AST12345	
	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%
UDF	62.50	92.59	75.00	96.77	85.00	100.00	82.50	91.67	72.41	91.30	79.31	95.83	75.86	91.67	79.31	92.00
UOF	58.33	58.33	66.67	72.73	41.67	38.46	83.33	31.25	70.00	100.00	100.00	47.62	80.00	57.14	80.00	61.54
LLF	75.00	42.86	87.50	50.00	87.50	58.33	87.50	58.33	100.00	70.00	100.00	63.64	100.00	77.78	100.00	87.50
SS3	66.67	30.00	55.56	20.83	66.67	23.08	33.33	20.00	71.43	21.74	42.86	13.64	42.86	20.00	42.86	20.00
SS2	47.22	38.64	41.67	35.71	36.11	35.14	11.11	23.53	41.67	50.00	41.67	31.25	37.50	40.91	41.67	45.45
SS1	62.00	63.27	62.00	65.96	58.00	60.42	68.00	51.52	59.38	55.88	9.38	30.00	50.00	45.71	50.00	48.48
DGP	63.16	48.98	68.42	55.32	63.16	61.54	57.89	51.16	42.31	68.75	38.46	52.63	34.62	64.29	38.46	62.50
CUP	66.00	86.84	66.00	91.67	68.00	91.89	66.00	89.19	63.64	77.78	63.64	77.78	42.42	73.68	45.45	75.00
AGF	50.79	76.19	53.97	80.95	58.73	75.51	49.21	75.61	54.17	68.42	37.50	64.29	47.92	65.71	52.08	67.57
BAS	90.91	62.50	90.91	66.67	90.91	83.33	90.91	76.92	80.00	34.78	80.00	40.00	70.00	28.00	90.00	34.62
BUL	92.86	72.22	100.00	66.67	100.00	73.68	92.86	86.67	100.00	75.00	100.00	52.17	100.00	48.00	100.00	54.55
WAT	52.63	100.00	57.89	100.00	57.89	100.00	84.21	100.00	100.00	100.00	100.00	100.00	90.91	100.00	100.00	100.00
NVW	94.12	66.67	94.12	76.19	94.12	59.26	82.35	58.33	100.00	87.50	100.00	87.50	100.00	77.78	100.00	87.50
OCA	62.67		65.40		62.67		62.67		64.45		55.86		57.42		60.94	
KAP	58.69		61.76		58.64		58.65		60.70		51.73		53.09		56.89	
VOCA	59.15		61.76		58.17		57.84		58.80		48.61		51.39		54.17	
VKAP	53.20		56.25		52.11		51.69		53.19		42.62		45.28		48.16	

Note: OCA% and KAP% are overall classification accuracy and kappa coefficient for the 13 land cover classes; VOCA% and VKAP% are overall classification accuracy and kappa coefficient for the 9 vegetation classes, excluding the four non-vegetated classes; PA% and UA% are producer's and user's accuracy.

Table 6 summarizes the accuracy assessment results based on six land cover classes. Overall, the SPOT data provide better classification accuracies than TM and ASTER data. Pasture and agroforestry classes have relatively poorer classification accuracies than other land cover classes. The SPOT-Fusion routine provides better classification accuracies for land cover classes than SPOT1234, implying that increasing spatial resolution but preserving the same spectral resolution improved the classification performance. Comparing TM2345 and TM-ALL, spectral bands were added but keeping the same spatial resolution, which cannot significantly improve classification. In this case, the accuracies for some classes such as pasture and water slightly improved, but for other classes such as primary forest and successional forest they decreased. In the different routines based on ASTER data, AST123 provides the poorest classification accuracy, but an addition of SWIR bands improves classification accuracies, indicating the importance of SWIR bands in land cover classification.

Table 6. Comparison of classification accuracies among different processing routines based on level I classification scheme

Class	SPOT HRG				Landsat TM				Terra ASTER							
	SPOT1234		SPOT-Fusion		TM2345		TM-ALL		AST-ALL		AST123		AST1234		AST12345	
	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%
PF	88.33	96.36	90.00	96.43	95.00	72.15	91.67	71.43	86.96	100.00	93.48	79.63	79.63	97.83	95.65	97.78
SS	86.32	73.87	88.42	73.68	71.58	68.00	70.53	65.05	92.06	72.50	76.19	72.73	72.73	90.48	90.48	77.03
PA	76.14	77.01	78.41	83.13	73.86	84.42	77.27	85.00	55.93	78.57	54.24	71.11	71.11	37.29	42.37	73.53
AL	58.11	74.14	59.46	78.57	58.11	78.18	55.41	77.36	65.52	64.41	56.90	67.35	67.35	63.79	65.52	61.29
BL	92.86	72.22	100.00	66.67	92.86	86.67	92.86	86.67	100.00	75.00	100.00	52.17	52.17	100.00	100.00	54.55
WB	86.11	91.18	83.33	93.75	86.11	75.61	91.67	84.62	100.00	94.74	100.00	94.74	94.74	100.00	100.00	94.74
OCA	78.75		80.38		75.48		75.48		77.73		72.66		74.61		75.78	
KAP	73.35		75.44		69.39		69.33		72.06		66.05		68.45		69.82	

Overall, this research indicates that increased spatial resolution such as SPOT data can improve land cover or vegetation classification accuracies. This is because increased spatial resolution can reduce mixture pixels. However, the increased spectral variation within the intra-class caused by high spatial resolution compensate for the benefits from the reduction of mixture pixels, resulting in decreased accuracy. This may imply that per-pixel based classification approach is not very suitable for high spatial resolution image classification. Texture or contextual based classification, or object-oriented classification approaches may be better suitable for SPOT image classification.

5. CONCLUSION

The findings listed above corroborate the difficulty in land cover classification, especially vegetation classification, when using optical sensor data for moist tropical areas. No sensor data or image processing routine can provide the best classification accuracy for all land cover classes. Overall, SPOT data fusion image with 5 m spatial resolution provide the best classification accuracy for 13 and 6 land cover classes or 9 vegetation classes. Increasing spatial resolution is useful for improving classification accuracy. Increasing highly correlated spectral bands cannot improve classification accuracy, but SWIR bands are important for such task. The classification for SS2 and SS3 are especially difficult because of the confusion between successional stages and agroforestry.

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