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A comparative analysis of approaches for successional vegetation classification in the Brazilian Amazon

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Research on separation of successional stages has been an active topic for the past two decades because successional vegetation plays an important role in the carbon budget and restoration of soil fertility in the Brazilian Amazon. This article examines classification of successional stages by conducting a comparative analysis of classification algorithms (maximum likelihood classifier – MLC, artificial neural network – ANN, K-nearest neighbour – KNN, support vector machine – SVM, classification tree analysis – CTA, and object-based classification – OBC) on varying remote-sensing data-sets (Landsat and ALOS PALSAR). Through this research we obtained the following four major conclusions: (1) Landsat data provide higher classification accuracy than ALOS PALSAR data, and individual PALSAR data cannot effectively separate successional stages; (2) Fusion of Landsat and PALSAR data provides better classification than individual sensor data; (3) Depending on the data-set, the best classification algorithm varies, MLC and CTA are recommended for Landsat or fusion images; and KNN is recommended for the combination of Landsat and PALSAR data as extra bands; (4) the MLC based on fusion images is recommended for vegetation classification in the moist tropical region when sufficiently representative training samples are available.

Keywords: successional vegetation; Brazilian Amazon; nonparametric classification algorithms; Landsat; ALOS PALSAR

1. Introduction

The colonization projects initiated in the 1970s and their subsequent associated road construction are major factors resulting in high deforestation in the Brazilian Amazon (Moran 1981; Laurance et al. 2004). The past four decades of deforestation has converted a vast area of mature forest into a mosaic of agricultural lands, pasture and successional vegetation (Roberts et al. 2002; Neeff et al. 2006; Lu et al. 2012). Successional vegetation is the regrowth of forest in deforested regions and there is not an obvious boundary between adjacent successional stages. In the Amazonian deforested regions, successional vegetation plays an important role in the carbon budget and soil fertility restoration due to its increasing area and high growth rate (Feldpausch et al. 2004; Orihuela-Belmonte et al. 2013). However, due to the large differences in biomass within successional stages, large

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uncertainties are created when successional vegetation is mapped as a homogenous group. Successional stages have a large variation in biomass density from less than 2 kg/m^2 in initial stages to greater than 20 kg/m^2 in advanced successional stage (Vieira et al. 2003; Lu 2005) due to the influence of soil fertility, land-use history and vegetation age. It is necessary to separate stages of successional vegetation and map their spatial distribution to reduce the uncertainty in carbon budget estimation.

In general, successional vegetation can be grouped into three stages – initial (SS_1), intermediate (SS_2) and advanced (SS_3) successional stages based on field measurements (Tucker, Brondizio, and Moran 1998; Lu et al. 2003) or remote-sensing data (Moran and Brondízio 1998; Lu 2005; Li et al. 2011; Lu et al. 2012). Different successional stages have their own characteristics in vegetation-stand structure (Moran and Brondízio 1998; Lu et al. 2003). As shown in Figure 1, SS_1 is initially characterized by dominance of grasses, herbaceous plants, vines and saplings (Figure 1a). Saplings are the main structural element in SS_1 and represent the majority of the aboveground biomass. The vegetation structure in SS_2 provides a mixture of dense sapling and young tree with higher canopy than SS_1 and a small internal difference between canopy and understory individuals (Figure 1b). In SS_3, trees occupy the canopy and present obvious stratification of forest-stand structure (Figure 1c). A detailed description of successional stages is provided in Lu (2005).

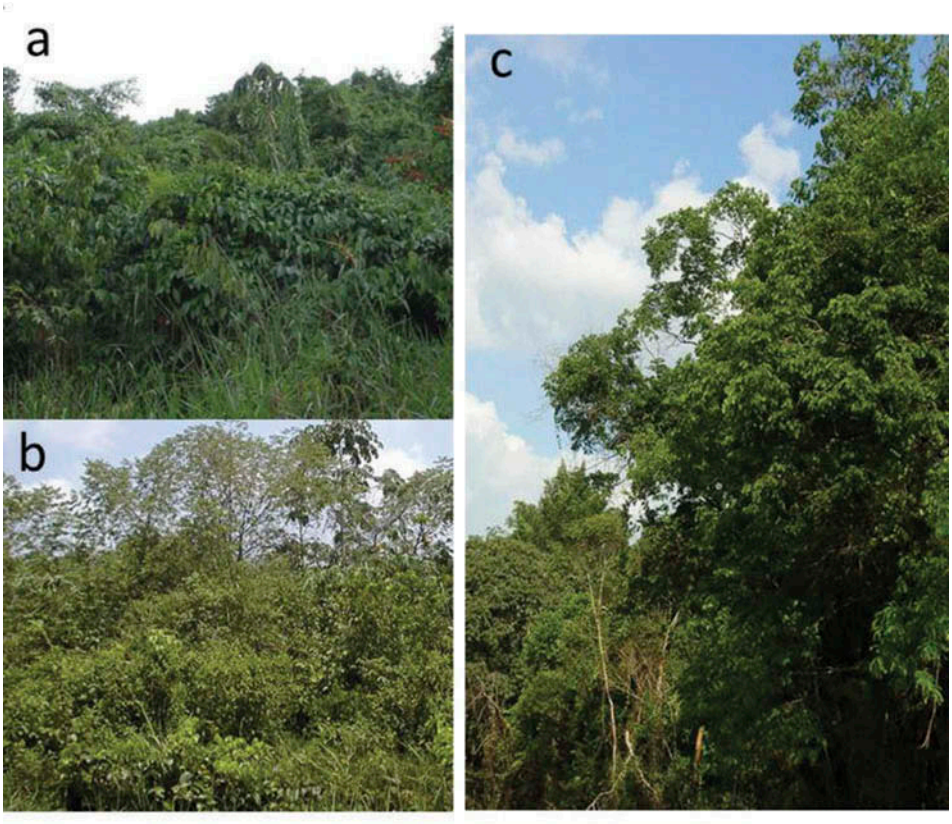

Figure 1. A comparison of initial (SS_1 – a), intermediate (SS_2 – b) and advanced (SS_3 – c) successional stages.

Remote-sensing data have unique characteristics (e.g. radiometric, spectral, spatial and temporal resolutions for optical sensor data and polarization options for radar data) to represent land-surface features, and have become primary data source for land cover or vegetation classification at various scales (Lu and Weng 2007; Aguirre-Salado et al. 2012; Johnston, Henry, and Gorchov 2012; Gong et al. 2013). Scientists have made great efforts using remotely sensed data for mapping stages of successional vegetation in the past two decades (Foody and Curran 1994; Moran et al. 1994; Palubinskas et al. 1995; Foody et al. 1996; Kimes et al. 1999; Salas et al. 2002; Castro, Sanchez-Azofeifa, and Rivard 2003; Vieira et al. 2003; Aguilar 2005; Kennaway and Helmer 2007; Galvão et al. 2009; Mello and Alves 2011; Li, Lu, Moran, Dutra et al. 2012; Lu et al. 2012). During the image classification procedure, selection of suitable remote-sensing variables and development of advanced classification algorithms have long been two active research topics to improve land-cover classification performance when training samples are available (Lu et al. 2012).

Although spectral signature has been recognized as the most important feature in land-cover classification, spatial information inherent in remote-sensing images also provides valuable information for improving classification (Li et al. 2011; Lu et al. 2012). Texture-based methods are commonly used to effectively employ spatial information in a classification procedure. Of the many texture metrics available (e.g., Haralick, Shanmugam, and Dinstein 1973; Marceau et al. 1990; Chen, Stow, and Gong 2004), the GLCM-based (grey-level co-occurrence matrix) texture measure is the most commonly used and has been extensively applied to land-cover classification (Marceau et al. 1990; Johansen et al. 2007; Li, Lu, Moran, Dutra et al. 2012; Wood et al. 2012).

As many types of remote-sensing data are available, it is important to effectively employ their varying features. Data fusion of different spatial resolution or sensor data can be used to integrate multispectral and panchromatic or radar data into a new data-set with improved spatial resolution while preserving multispectral features (Zhang 2010; Lu et al. 2011). The majority of data fusion techniques have been summarized in previous literature (e.g., Pohl and van Genderen 1998; Ehlers et al. 2010; Zhang 2010; Kandrika and Ravisankar 2011). In particular, the integration of optical and radar data-sets has been regarded effective in providing more new information than an individual data-set because of their different capabilities to capture land-surface features (Rignot, Salas, and Skole 1997; Lu et al. 2011; Pereira et al. 2013).

Many classification algorithms from traditional parametric such as maximum likelihood classifier (MLC) to non-parametric algorithms such as support vector machine (SVM), classification tree analysis (CTA), K-nearest neighbour (KNN) and artificial neural network (ANN) (Lu and Weng 2007; Tso and Mather 2009) can be used for vegetation classification. The majority of the classification methods are per-pixel-based assigning each pixel into a category and the results can be noisy due to the heterogeneity of a landscape (Lu and Weng 2007). An alternative to pixel-based classification is to use object-based classification (OBC) (Walter 2004; Mallinis et al. 2008; Blaschke 2010). Because of the difficulty in identifying an optimal algorithm for a specific study, a comparative analysis of different classification algorithms is often conducted (Li, Lu, Moran, and Sant'Anna 2012; Lu et al. 2012; Li, Im, and Beier 2013; Rosa and Wiesmann 2013; Cracknell and Reading 2014).

Our team has conducted research on land-use/cover classification in the moist tropical regions of the Brazilian Amazon in the past decade (see overviews by Lu et al. (2012)). We have examined multiple remote-sensing variables from Landsat, ASTER, SPOT, radar (e.g. ALOS PALSAR L-band and Radarsat C-band) and their combination, and explored

varying classification algorithms such as MLC, SVM, ANN and OBC for land-cover classification (Moran et al. 1994; Li, Lu, Moran, and Sant'Anna 2012; Lu et al. 2012). Based on our previous research, this article aims to provide a comparative analysis of data-sets and algorithms for vegetation classification in the Brazilian Amazon. This article's primary contributions are the identification of data-sets and classification algorithms to provide the best separation of successional stages, and new insights for using remote-sensing techniques to distinguish successional stages in other moist tropical regions in the world.

2. Description of the study area

Altamira located in the northern Brazilian State of Pará was selected (see Figure 1). The study area covers approximately 3000 km^2 and the dominant native vegetation is mature moist and liana forest. With the construction of the Transamazon Highway (BR-230) in the early 1970s, this population and older Caboclo settlers claimed land along the new highway and legalized their land claims. Major deforestation began in 1972, coincident with the construction of the Transamazon Highway (Moran 1981). In the past four decades, a large area of primary forest (e.g. mature moist and liana forest) was converted to successional vegetation, pasture and agricultural lands (Moran et al. 1994; Moran and Brondízio 1998; Li et al. 2011) (Figure 2).

Additional environmental features in the study site, Altamira include moderately rolling uplands with highest elevation of approximately 350 m. Floodplains along the Xingu River are flat with lowest elevation of approximately 10 m. Annual rainfall in Altamira is approximately 2000 mm, concentrating from late October through early June; the dry period occurs between June and September. The average temperature is about 26° C (Tucker, Brondizio, and Moran 1998). Because of the relatively long land-use history and good-quality soil conditions in Altamira, successional vegetation has a wide variation of biomass density with different vegetation ages (Lu 2005). Therefore, this study area is ideal to examine how remote-sensing data can be used to separate successional vegetation into stages.

3. Methods

3.1. Data collection and preprocessing

Landsat and ALOS PALSAR data were selected for use in the Altamira study area. The Landsat 5 TM imagery was acquired on 2 July 2008 and six multispectral bands with 30 m spatial resolution were used. The Landsat imagery was geometrically rectified into the *Universal Transverse Mercator* (*UTM*) projection, Zone 22 South and the resulting root mean square error (RMSE) of geometric co-registration was less than 0.5 pixels. An improved image-based dark object subtraction model was then used to implement radiometric and atmospheric corrections (Chavez 1996; Chander, Markham, and Helder 2009). The ALOS PALSAR FBD (fine beam double polarization) Level 1.5 product with HH and HV polarization options (ground range, unsigned 16-bit integral number, 12.5-m pixel spacing) was acquired on 2 July 2009. The PALSAR L-band HH and HV images were registered into UTM with a RMSE value of 1.02 pixels based on 28 control points. These images were resampled to a cell size of 10 m × 10 m using the nearest neighbour sampling method during the image-to-image registration. A Lee-Sigma with a 5 × 5 window size

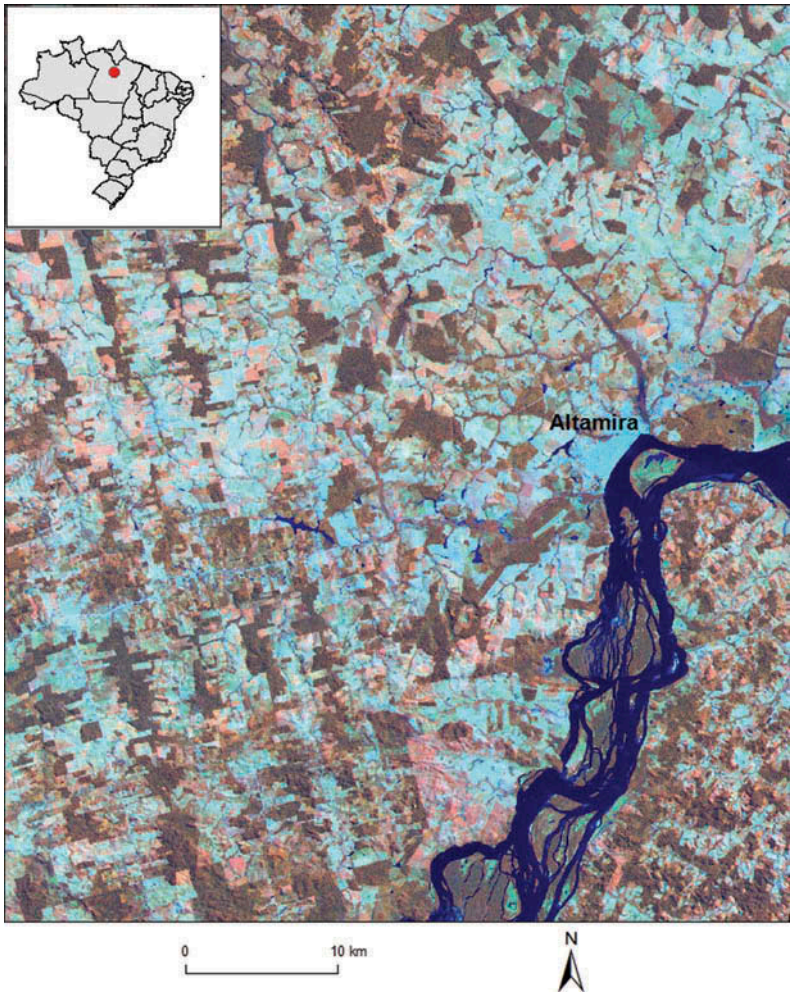

Figure 2. Study area in and around Altamira, Pará State, Brazil.

was used to reduce the speckles in the PALSAR imagery. A detailed description of image preprocessing for Landsat TM and PALSAR L-band data was provided in Lu et al. (2011).

In addition to the Landsat and PALSAR data, QuickBird imagery (acquired in 2008) and field survey data (collected in 2009) were used to collect a total of 432 sample plots. Approximately half of the sample plots (i.e. 220 plots) were randomly selected (based on the rule of minimum of 10 plots per class) for use as training plots during the image classification. The remaining 212 samples were used as test sample plots for accuracy assessment of the classified images. A detailed description of sample collection from field survey and QuickBird image was provided in our previous papers (Li et al. 2011; Lu et al. 2011). Thus, this article will not detail the data collection issue.

3.2. Comparison of different data-sets for vegetation classification

A common method to combine data-sets is to develop textural images from a radar image and incorporate the derived textural images as extra bands into multispectral image such

as Landsat TM. Our research group previously examined six GLCM-based texture measures (e.g. variance, homogeneity, contrast, dissimilarity, entropy and second moment) with six window sizes (5 × 5, 9 × 9, 15 × 15, 19 × 19, 25 × 25, and 31 × 31) based on ALOS PALSAR L-band HH and HV images, and identified textures SM25 (second moment with a window size of 25 × 25 pixels) and CON31 (contrast with a window size of 31 × 31 pixels) based on HH image and textures CON25 (contrast with a window size of 25 × 25 pixels) and SM19 (second moment with a window size of 19 × 19 pixels) based on HV image provided the best separability of vegetation types (Li, Lu, Moran, Dutra et al. 2012). Therefore, these textural images are directly used in this research.

An alternative to combining different sensor data is the use of a data fusion technique. Many data fusion methods, such as principal component analysis, wavelet-merging technique, intensity-hue-saturation (IHS), Brovey transform, Gram Schmidt fusion and Ehlers fusion, have been developed to integrate spectral and spatial information (Pohl and van Genderen 1998; Chen and Stow 2003; Ehlers et al. 2010; Zhang 2010). Our previous research indicated use of the wavelet-merging technique to integrate Landsat TM and ALOS PALSAR L-band HH image provided the best classification performance for land-cover classification in the Amazon (Lu et al. 2011). Therefore, this fusion image is directly used in this research.

To compare the capabilities and functions of remote-sensing data-sets, four data-sets, (1) Landsat TM multispectral bands, (2) ALOS PALSAR HH, HV and textures, (3) combination of TM multispectral bands and textural images from PALSAR HH and HV data as extra bands and (4) data fusion result with wavelet-merging method based on TM multispectral and ALOS PALSAR L-band HH data, were used. The classification results based on these four data-sets were evaluated using the error matrix approach.

3.3. Comparison of different algorithms for vegetation classification

Classification algorithms are categorized as parametric or non-parametric. The parametric, MLC is the most commonly used for land-use/cover classification due to its robust, simple and easy to use software which is available in almost all image processing software packages. In recent decades, the CTA, ANN, KNN and SVM are commonly used non-parametric algorithms. As stated previously, because most classification algorithms are conducted on a per-pixel-based spectral image, the classification results may be noisy (Li et al. 2011; Lu et al. 2011). OBC provides an alternative for classifying remotely sensed images into a thematic map based on segments comparing with the traditional per-pixel-based classification methods. Considering the classification algorithms commonly used in land-use/cover classification in recent years, six algorithms – MLC, CTA, ANN, KNN, SVM and OBC – were selected in this research and they are briefly summarized in Table 1. Detailed description of these approaches can be found in Tso and Mather (2009) and Li et al. (2011).

3.4. Comparative analysis of vegetation classification results

A comparative analysis of the classification results is necessary to identify the data-set and classification algorithm with the best performance. Based on our research objectives and the characteristics of the study area, a classification system with three forest classes (i.e. upland, flooding and liana), three successional stages (i.e. initial – SS_1, intermediate – SS_2 and advanced – SS_3), agropasture, and three non-vegetated classes (i.e. water, wetland and

Table 1. A summary of major characteristics of the classification algorithms.

Algorithms	Major characteristics
MLC	MLC assumes normal distribution for each feature of interest. It is based on the probability that a pixel belongs to a particular class and takes the variability of classes into account by using the covariance matrix.
CTA	CTA is a non-parametric statistical machine learning algorithm, having such advantages as distribution-free and easy interpretation over traditional supervised classifiers. The basic concept of a classification tree is to split a dataset into homogeneous subgroups based on measured attributes.
ANN	Fuzzy ARTMAP is one of the neural network classification methods, which synthesizes fuzzy logic and adaptive resonance theory (ART) models. It is a clustering algorithm operating on vectors by a fuzzy set of features, or a pattern of fuzzy membership values between 0 and 1 and consists of four layers of neurons: input, category, mapfield and output. It is controlled by a choice parameter α, learning rate parameters β_1 in ARTa and β_2 in ARTb, and vigilance parameters ρ_1 in ARTa and ρ_2 in ARTb. The ρ_1 and ρ_2 control the operation during learning and operational phases of the network and the mapfield weights and category layer weights are learnt adaptively during the process.
KNN	KNN is based on the minimum distance from image pixels to the training samples. Euclidean distance is often used to calculate the distance between two pixels. A suitable k value is crucial for a successful classification: a large k value reduces the effect of noise on the classification, but makes boundaries between classes less distinct; a small k value may not result in good classification accuracy.
OBC	OBC provides an alternative for classifying remotely sensed images into a thematic map based on segments comparing to the traditional per pixel-based classification methods. The whole classification process consists of three steps: (1) image segmentation – a moving window assesses spectral similarity across space and over all input bands, and segments are defined based on user-specified similarity threshold, (2) creation of training sites and signature classes based on image segments and (3) classification of the segments.
SVM	SVM is a relatively new supervised classifier for remote-sensing image classification, but has gained great attention in recent years. It separates the classes with a decision surface that maximizes the margin between classes. This surface is called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors. The support vectors are critical elements of the training set. The optimal hyperplane solution is achieved by different functions called kernels.

urban) were designed (Lu et al. 2011; Li, Lu, Moran, Dutra et al. 2012). The same training sample data were used for land-cover classification in each data-set and each selected classification algorithm. Because the objective of this research is the separation of successional vegetation stages, the comparative analysis is only on the three successional stages, that is, SS_1, SS_2 and SS_3.

The error matrix method is used to evaluate land-cover classification results. This method provides a detailed assessment of the agreement between the classified result and reference data, and provides information on how the misclassification occurred (Congalton 1991; Congalton and Green 2008; Foody 2009). Because the accuracy assessment for vegetation classes in this research is partially based on our previous work on land-cover classification (Lu et al. 2011), we used the following methods to calculate the accuracy for each successional stage and overall vegetation classification accuracy:

$$\text{Average accuracy for each successional stage } (AA_{ss}) = (PA + UA)/2,$$

$$\text{Overall average accuracy } (OAA) = (AA_{ss_1} + AA_{ss_2} + AA_{ss_3})/3,$$

where PA and UA represent producer's accuracy and user's accuracy, respectively, for each successional stage, i.e. SS_1, SS_2 and SS_3, which were calculated from the error matrix. In an ideal situation, both high PA and UA values represent accurate classification in this specific type. Thus, the AA_{ss} can be used as an indicator to show the classification accuracy for a specific vegetation type. The OAA can be used to express the overall vegetation classification performance.

4. Results and discussion

4.1. Analysis of classification results from different data-sets

This research indicated Landsat data provided higher classification accuracy than ALOS PALSAR data, and integration of Landsat and PALSAR data with the wavelet-merging techniques further improved classification accuracy no matter which classification algorithm was used. However, the combination of Landsat and PALSAR-derived textures as extra bands may or may not improve classification depending on the classification algorithm (see Table 2). Optical multispectral image has high classification performance for successional stages. This is because the optical sensor mainly captures land-surface features and its spectral signature can represent the change of forest-stand structure as vegetation grows (Lu 2005). However, the backscattering coefficients in radar data (e.g. ALOS PALSAR here) capture the roughness of land surfaces, and cannot effectively represent the difference of vegetation-stand structures. Therefore, radar data alone cannot

Table 2. A comparison of classification algorithms and data-sets for successional vegetation classification results in Altamira, Para State, Brazil.

			Classification algorithms					
Accuracy	Data-set	SS	MLC	CTA	ARTMAP	KNN	OBC	SVM
AA_{ss}	TM	SS_1	57.9	63.8	62.0	60.2	56.5	50.2
		SS_2	81.3	76.7	74.8	83.3	86.6	72.9
		SS_3	85.7	87.7	48.5	84.7	88.5	59.2
	PALSAR	SS_1	46.1	49.2	41.0	41.8	47.7	58.7
		SS_2	65.4	68.1	55.3	43.4	65.4	48.8
		SS_3	31.2	19.7	31.2	22.9	32.0	23.8
	Combination	SS_1	57.4	57.4	54.8	66.7	57.3	55.9
		SS_2	84.2	75.9	47.2	82.8	80.1	80.2
		SS_3	59.1	65.2	26.2	87.5	74.5	63.8
	Fusion	SS_1	75.2	71.9	63.2	63.8	65.2	61.3
		SS_2	89.4	89.9	89.9	89.4	89.4	80.2
		SS_3	88.5	90.5	93.1	84.7	92.0	82.1
OAA	TM		75.0	76.0	61.8	76.0	77.2	60.8
	PALSAR		47.5	45.6	42.5	36.0	48.3	43.7
	Combination		66.9	66.2	42.7	79.0	70.6	66.6
	Fusion		84.4	84.1	82.0	79.3	82.2	74.5

Note: Average accuracy for each successional stage (AA_{ss}) = (PA + UA)/2.
Overall average accuracy = $(AA_{ss_1} + AA_{ss_2} + AA_{ss_3})/3$.

provide satisfactory vegetation classification. Because of the different features of optical sensor and radar data, integration of both data-sets using suitable fusion techniques may combine the strengths of optical and radar data into one data-set, thus providing more information than individual sensor data. However, a simple combination of Landsat and PALSAR data as extra bands had little increase in performance for successional stages due to the poor performance of radar data. Figure 3 provides a comparison of vegetation distributions using the MLC based on four data-sets showing the accurate results of fusion image and poor capability of radar image for vegetation classification.

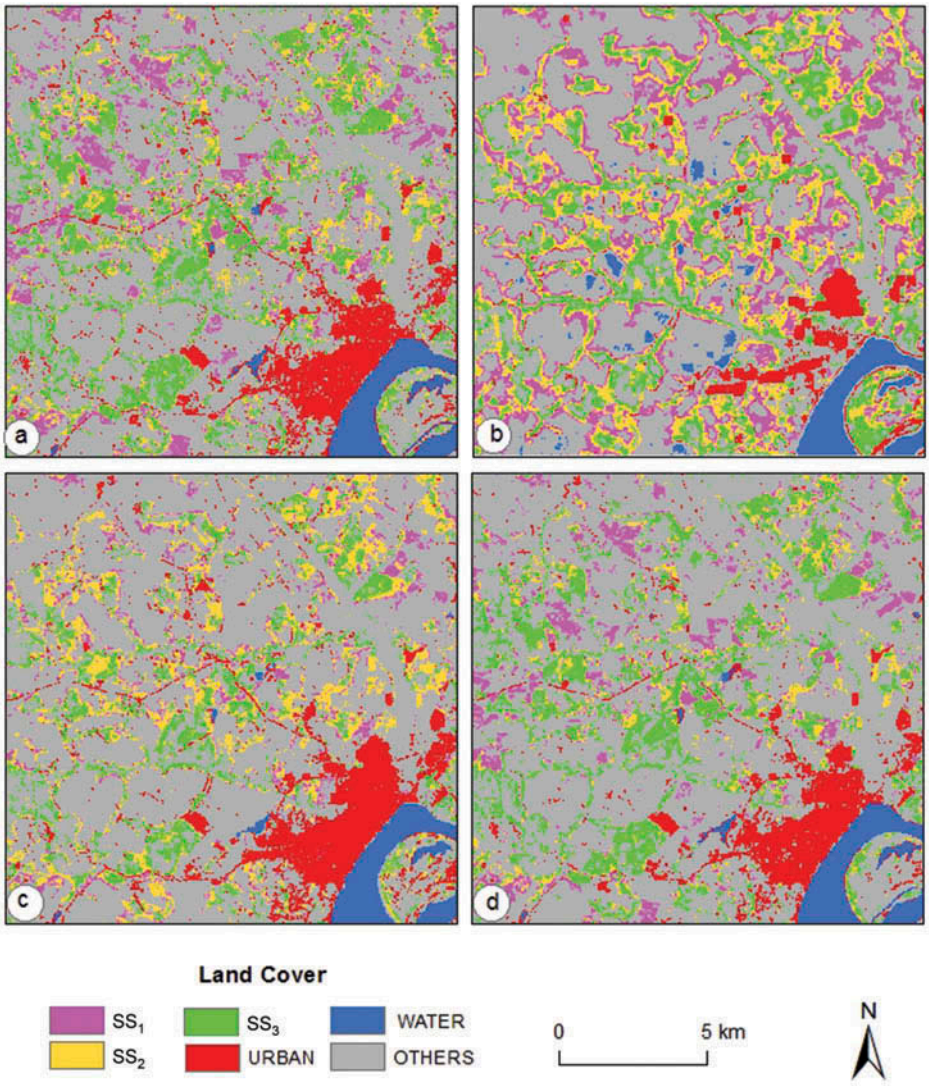

Figure 3. Comparison of classification results among different data-sets using maximum likelihood classifier (a – Landsat TM multispectral image; b – ALOS PALSAR data; c – combination of TM and PALSAR data; d – fusion of TM multispectral and PALSAR L-band HH image).

4.2. Analysis of classification results using different algorithms

For accuracy in individual classification algorithm for a data-set, if the classification accuracy from the MLC is used as a baseline, non-parametric classification algorithms cannot guarantee improvement in vegetation classification for Landsat multispectral or fused multispectral images. Some algorithms such as SVM and ARTMAP produced lower classification accuracy than the MLC for four data-sets. For Landsat TM imagery, CTA, KNN and OBC only slightly improved classification accuracy compared to MLC. For PALSAR data, only OBC has higher classification accuracy than MLC. For the combination of Landsat and PALSAR as extra bands, only KNN and OBC improved classification accuracy. In contrast, for the fusion data-set all the non-parametric algorithms have poorer performance than MLC. Table 2 indicates no one algorithm can provide best vegetation classification for different remote-sensing data. A synthetic analysis of Table 2 indicated MLC provided high classification results compared with non-parametric algorithms, especially for TM multispectral data and the fused image. Some non-parametric algorithms such as OBC and KNN provided better classification than MLC, but it is critical to identify optimal parameters used in relevant algorithms. Improper parameterization may reduce vegetation classification.

4.3. Comparative analysis of classification results from different data-sets using various classification algorithms

Comparing the individual successional stage, no algorithm can provide the best accuracy for all successional stages based on different data-sets. For Landsat TM multispectral image, CTA provided the best result for SS_1, but OBC provided the best result for SS_2 and SS_3, implying the importance of reducing the spectral variation in complex forest-stand structure to improve classification. For PALSAR data, SVM provided the best for SS_1 and CTA the best for SS_2, but all selected algorithms had poor performance for SS_3 with accuracy of less than 32%. This implies radar data are unable to separate vegetation types, especially the SS_3 because of its similar stand structure to mature forest, that is, similar roughness of forest canopy. For the combination of TM and PALSAR data, KNN provided the best for SS_1 and SS_3, but MLC for SS_2. Interestingly, all non-parametric classification algorithms have lower performance than MLC for the separation of SS_2 from other vegetation types. For the fusion image, MLC provided the best for SS_1, and ARTMAP provided the best for SS_2 and SS_3. This research indicates algorithms have various performances for succession stages, implying the necessity to combine results into a new thematic map ensuring the best result for each class. Figure 4 provides examples for a comparison of classification results based on the fusion image using different classification algorithms, showing different spatial patterns of vegetation classification.

Above classification results indicated no one single data-set and no one algorithm can provide the best results for all vegetation types. A potential solution is to combine results from data-sets or algorithms. Previous research has indicated the potential of assembling classification results from variables or algorithms to further improve classification results (Waske and Braun 2009; Ceamanos et al. 2010; Chitroub 2010; Zhu 2010; Du et al. 2012). However, it is critical to develop suitable rules to perform this integration.

Our research indicated the challenge in separating vegetation stages using individual sensor data due to complex-stand structure. Because different sensor data – optical, radar, and LiDAR – have various capabilities in capturing forest-stand attributes, this research showed the importance of integrating optical and radar to improve vegetation

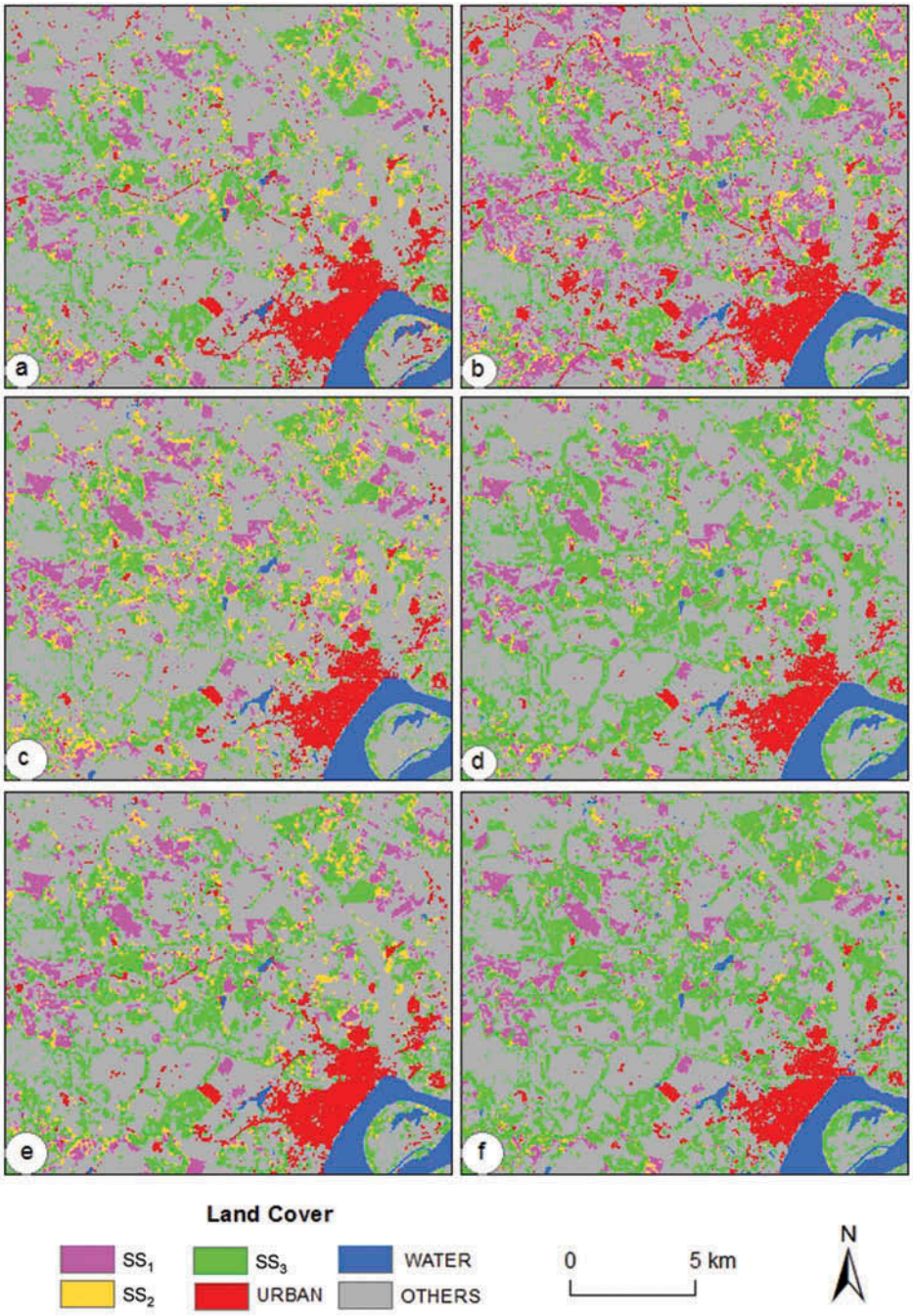

Figure 4. Comparison of classification results based on fusion image using different classification algorithms (a – MLC; b – CTA; c – ARTMAP; d – KNN; e – OBC; f – SVM).

classification. Since LiDAR has the capability to provide tree or canopy height information (Castillo et al. 2012), the integration of LiDAR and optical (and/or radar) may be valuable to improve vegetation classification. However, incorporation of LiDAR data and

optical or radar data for improving vegetation classification has not been extensively used because of the constraints of availability of LiDAR data.

5. Summary

Although mapping of successional vegetation distribution has gained increased attention in the past two decades because of its importance in reducing carbon budget uncertainty and restoration of soil conditions, accurate separation of successional stages is still a challenge. Through this research, the following conclusions can be obtained:

(1) Remote-sensing data – Landsat TM provided higher classification accuracy than ALOS PALSAR, and integration of both data-sets using wavelet-merging techniques improved classification performance of successional stages;
(2) Classification algorithms – MLC provides reasonable good classification accuracy, and some non-parametric algorithms improved classification, but optimization of relevant parameters in the algorithm is critical;
(3) No single remote-sensing data or classification algorithm can provide the best accuracy for each successional stage, implying the importance of combining classification results into a new result through certain rules;
(4) When representative training samples for vegetation types are available, MLC based on the fusion image of Landsat TM and ALOS PALSAR data provided the best classification result and is recommended for vegetation classification in the moist tropical region.

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