A COMPARISON OF MAXIMUM LIKELIHOOD CLASSIFIER AND OBJECT-BASED METHOD BASED ON MULTIPLE SENSOR DATASETS FOR LAND-USE/COVER CLASSIFICATION IN THE BRAZILIAN AMAZON

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ABSTRACT:

Majority of land use/cover classification studies are based on the use of spectral signatures at the per-pixel level, while ignoring spatial features inherent in an image. The maximum likelihood classifier (MLC) may be the most common classification method in practice, but the object-based classification (OBC) method has been obtained increasingly attention due to its capability of incorporating spatial information in a classification procedure. This paper provides a comparison of MLC and OBC based on different datasets – Landsat Thematic Mapper (TM), ALOS PALSAR L-band, and their combinations. Through comparative analysis of the classification results, we found that the OBC method cannot significantly improve overall land use/cover classification accuracy comparing with the maximum likelihood classification, but it indeed improve some vegetation classes having complex forest stand structure, and the OBC method is especially valuable for higher spatial resolution images. Also the OBC method has better performance than MLC when a combination of Landsat TM and PALSAR L-band data as extra bands is used.

1. INTRODUCTION

Many algorithms, from traditional per-pixel based parametric algorithms (e.g., maximum likelihood classification), to advanced nonparametric algorithms (e.g., neural network, decision tree classification, and support vector machine), and to object-based algorithms, have been used to classify remotely sensed data into land use/cover thematic maps (Lu and Weng, 2007). Most of previous studies are based on the use of spectral signatures at per-pixel level, ignoring the use of spatial features inherent in an image. However, previous studies also have indicated the importance of using spatial features in the classification procedure in improving land use/cover classification, especially when high spatial resolution images are used (Lu *et al.*, 2010). Different methods can be used to incorporate the spatial features into the classification procedure. One common method is to develop texture images with suitable texture measures (Lu *et al.*, 2008; Li *et al.* 2011). The critical in using textural images is to identify suitable texture measures, as well as proper window sizes, image band, etc. In practice, it is often time-consuming and challenging to identify optimal textural images for a given study area (Li *et al.*, 2011). The problem in using textural images is that texture is often site-dependent, that is, the same texture used in one study area cannot guarantee suitable in another landscape for land use/cover classification. Therefore, comparing with spectral signatures, textural images are not extensively applied in image classification, especially for medium or coarse spatial resolution image.

Another common method to use spatial information is the object-based classification (OBC) method, which is the focus of this research. Unlike the per-pixel based classification algorithms, the OBC method is first to partition the raster image into segments with spatially continuous and homogeneous regions, and then classify the segments into land use/cover classes (Blaschke, 2010). Previous studies using OBC for land use/cover classification are mainly based on spectral signatures. How OBC can improve land use/cover classification based on different remotely sensed data sources has not been fully examined. Therefore, the objective of this paper is to conduct a comparative analysis of maximum likelihood classifier (MLC) and OBC for land use/cover classification based on different datasets, such as Landsat Thematic mapper (TM), radar data (ALOS PLASAR L-band data here), and combination of both datasets by using PALSAR L-band data as extra bands and by using a data fusion technique, in order to better understand the performance of OBC in different data sources with various spatial resolutions.

2. STUDY AREA

The study area is located in a moist tropical region of the Brazilian Amazon – Altamira, along the Transamazon Highway (BR-230) in the northern Brazilian state of Pará (Figure 1). The study area covers approximately 3,116 km^2. The dominant native vegetation types are mature moist forest and liana forest. Major deforestation began in the early 1970s, coincident with the construction of the Transamazon Highway (Moran, 1981). Extensive deforestation since the 1980s has led to a complex landscape consisting of different succession stages, pasture, and agricultural lands (Moran *et al.*, 1994; Moran and Brondizio, 1998; Lu *et al.*, 2011). Different stages of successional vegetation are distributed along the Transamazon Highway and feeder roads. Annual precipitation in this study area is approximately 2,000 mm and is concentrated from late October through early June; the dry period lasts from June to September. Average temperature is about 26^oC.

3. METHODS

The framework of land use/cover classification based on different remotely sensed datasets is illustrated in Figure 2. The major steps include image preprocessing (radiometric and atmospheric calibration for Landsat TM image, image-to-image registration between Landsat TM image and PALSAR L-band data), design of different data scenarios, land use/cover classification with MLC and OBC, and comparison and evaluation of the classified results.

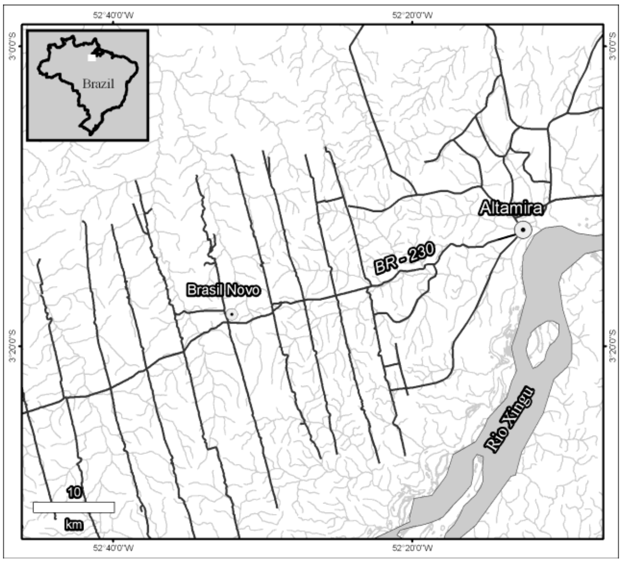

Figure 1. Study area – Altamira, Pará State, Brazil

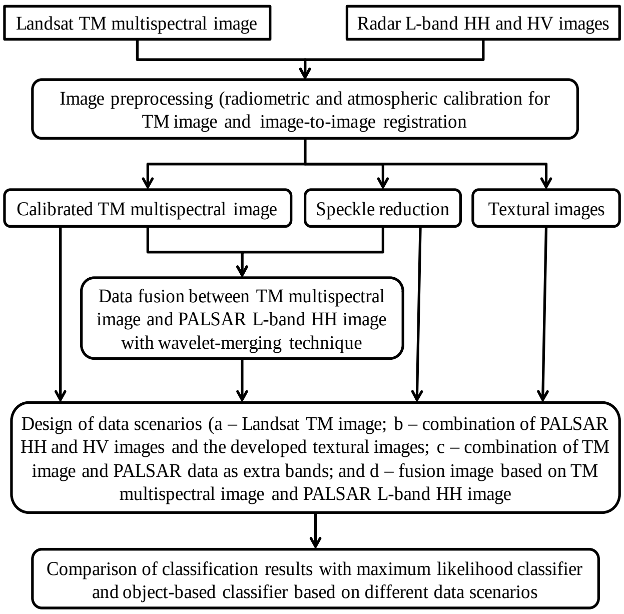

Figure 2. Framework of land use/cover classification with Landsat TM and ALOS PALSAR data

3.1 Data Collection and Preprocessing

Selection of a sufficient number of training and test samples are critical for land use/cover classification. In this research, sample plots for different land covers, especially for different stages of secondary succession (SS) and pasture were collected in the Altamira study area during July and August 2009. Meanwhile, a QuickBird image, which was acquired in 2008, was used to assist the selection of more training and test samples. The sample plots were used to create representative Region of Interest (ROI) polygons. A total of 432 sample plots were collected, including 220 ROIs for use as training sample plots for image classification and another 212 ROIs for use as test sample plots for accuracy assessment. A classification system consisting of three forest classes (upland [UPF], flooding [FLF], and liana [LIF]), three succession stages (initial [SS1], intermediate [SS2], and advanced [SS3]), agropasture (AGP), and three non-vegetated classes (water [WAT], wetland [WET], and urban [URB]) were designed (Lu *et al.*, 2011).

Landsat 5 TM image with 30 m spatial resolution, ALOS PALSAR L-band image with 12.5 spatial resolution, and QuickBird image with 0.6 m spatial resolution after data fusion with wavelet-merging technique were used in this research. The TM image, which was acquired on 2 July 2008, was geometrically registered to a previously corrected Landsat 5 TM image with Universal Transverse Mercator coordinate system (zone 22, south). An improved image-based dark object subtraction model was used to perform radiometric and atmospheric correction for Landsat TM image (Chavez, 1996; Lu *et al.*, 2002; Chander *et al.* 2009). The ALOS PALSAR FBD (Fine Beam Double Polarization) L1.5 products with HH and HV polarization options with 12.5-m pixel spacing were used. The PALSAR L-band images were acquired on 2 July 2009. The L-band images were registered to the 2008 Landsat 5 TM image with root mean square error of 1.020 pixels. The radar images were resampled to a pixel size of 10x10 m with the nearest neighbor technique during the image-to-image registration. The Lee-Sigma method with a window size of 5x5 was employed to reduce speckle on the PALSAR data (Lee *et al.*, 1994; Li *et al.*, 2012).

3.2 Design of Data Scenarios for Land Use/Cover Classification

In order to effectively use both TM and PALSAR data, one common method to combine multi-sensor data is to develop textural images from a radar image and to incorporate them into multispectral image as extra bands. Our previous research has indicated that the best combination of textural images for HH image was the textures SM25 (second moment with a window size of 25 by 25 pixels) and CON31 (contrast with a window size of 31 by 31 pixels), and the best combination for HV image is the textures CON25 (contrast with a window size of 25 by 25 pixels) and SM19 (second moment with a window size of 19 by 19 pixels) (Li *et al.* 2012). Therefore, they were directly used in this research. Figure 3 provides a comparison of radar radiometric and textural images, indicating the different features in reflecting land surfaces.

Another method to combine multi-sensor data is to use a suitable data fusion method to integrate Landsat TM and PALSAR image into a new multispectral image with improved spatial resolution. Since the wavelet-merging technique was regarded as the valuable approach to integrate optical and radar data in improving land use/cover classification (Lu *et al.*, 2011), this approach was used in this research to integrate TM multispectral and PALSAR L-band HH polarization image into a fused image with 10 m pixel spacing. A detailed description of the wavelet-merging technique is provided in Lu *et al.* (2011).

Based on the Landsat TM, PALSAR, and the derived images, four scenarios – (1) Landsat TM multispectral bands; (2) ALOS PALSAR HH, HV and the selected textural images; (3) combination of TM multispectral bands and PALSAR-based textural images as extra bands; and (4) the fusion image by using wavelet-based merging techniques based on both TM multispectral and PALSAR L-band HH image, were designed.

3.3 Land Use/Cover Classification with Maximum Likelihood Classifier and Object-based Classifier

MLC is the most common parametric classifier which assumes normal or near normal spectral distribution for each feature of interest. This classifier 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 (Jensen, 2005). Based on the field survey and a 2008 QuickBird image, a total of 220 sample plots (over 3,500 pixels) covering the 10 land cover types, each consisting of 15–30 plots, were used for image classification. In practice, the classification results from per-pixel based method often appear noisy because only pixel-based spectral features are used in the classification procedure, without including spatial information inherent in remote sensing data.

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 OBC classification process consists of three steps (Jensen, 2005): (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 thresholds, (2) creation of training sites and signature classes based on image segments, and (3) classification of the segments. This is done with the assistance of a reference image, which is an already classified image and is used to assign the majority class within each segment.

In this OBC method, one critic step is to develop a suitable segmentation image. Segmentation is the process partitioning an image into isolated objects so that each object shares a homogeneous spectral similarity (Blaschke *et al.*, 2004). These objects have better representative in the landscape than do the original pixels. The objects can be derived from image data and they are then analyzed using traditional classification methods such as minimum distance and MLC (Jensen, 2005; Lu *et al.*, 2010). Different segmentation algorithms such as Split and Merge, Watershed, and Markov Random Field were developed (Yu *et al*., 2006; Blaschke, 2010). In this research, the Watershed delineation approach was used. Different segmentation parameters (window size, weight mean factor, similarity tolerance and weight variance factor) based on different datasets were examined. The segment images were compared with visual inspection in order to identify the optimal parameters for segment image corresponding to different dataset. After the segment image was selected for each dataset, training sites (polygons), which coincide to the sample sites used in MLC, were selected. The classified image from MLC based on the training segments was used as a reference image.

3.4 Evaluation of Land Use/Cover Classification Results

The error matrix method is often used for evaluation of land-cover classification results. This method provides a detailed assessment of the agreement between the classified result and reference data (Congalton and Green, 2008). Other accuracy assessment parameters, such as overall classification accuracy, producer's accuracy, user's accuracy, and kappa coefficient are calculated from the error matrix, as much previous literature has described (e.g., Congalton, 1991; Congalton and Green, 2008; Foody, 2002, 2009). In this study, a total of 212 test sample plots from the field survey and a 2008 QuickBird image were used for accuracy assessment, with 12–33 plots for each land cover. An error matrix was developed for each classified image, producer's accuracy and user's accuracy for each class and overall accuracy and kappa coefficient for each classified image were calculated from the relevant error matrix.

4. RESULTANT ANALYSIS AND DISCUSSION

The classification results by using MLC based on different datasets are illustrated in Figure 4. It indicates the significantly different classification performance between Landsat TM and ALOS PALSAR data. One obvious feature in the classification results is that urban areas cannot be effectively separated from vegetation types based on the PALSAR data. The quantitative evaluation of the classification results are summarized in Table 1. For Landsat TM multispectral image, both MLC and OBC have similar overall accuracy with 81.1% – 81.6%, but OBC slightly improved SS2 and SS3 classification accuracies. For PALSAR data, OBC improved overall accuracy by approximately 1% compared to MLC, and OBC mainly improved FLF, LIF and AGP classes. Overall, PALSAR data have much poorer capability of land use/cover classification than TM multispectral image, with only 56.1%–57.1% v.s. 81.1%–81.6%. For the combination of TM and PALSAR-derived textural images, MLC even reduced classification accuracy, but OBC remained similar accuracy comparing with the results from Landsat TM image. On the other hand, when TM and PALSAR are fused with the wavelet-based method, the overall accuracies for both MLC and OBC increased by 4.3% – 4.8% comparing with individual TM image. The fusion images are especially valuable for vegetation types such as UPF, LIF, SS1, SS2, and SS3.

The results in Table 1 imply that MLC can provide reasonably good classification results when the data sets meet the requirement of normal distribution, such as in Landsat TM multispectral bands or data fusion results. When multiple source data are used, such as radar radiometric and textural images are combined as extra bands into multispectral image, use of MLC may reduce the classification performance. In this case, use of nonparametric algorithms, such as decision tree classifier, may provide better classification, as previous research indicated (Li *et al.*, in review). This research also indicated OBC is more effective for improving forest classification accuracy with complex forest stand structure when higher spatial resolution images are used, such as the data fusion image in this research. The OBC method seems not effective for medium spatial resolution images, but as spatial resolution increases, OBC can significantly improve land use/cover classification performance, as previous research shown by using QuickBird imagery (Lu *et al.*, 2010).

5. CONCLUSIONS

This research indicates that Landsat TM multispectral image provided better land use/cover classification than ALOS PALSAR L-band data. Integration of TM multispectral and PALSAR L-band data through the data fusion method is valuable for improving classification performance by 4.3% – 4.8%. However, the combination of TM multispectral and PALSAR-derived textural images as extra bands may reduce classification performance if MLC was used. This research indicates that MLC is valuable for land use/cover classification when the remote sensing data have normal distribution, but not suitable for multiple source data due to the violation of normal distribution assumption. OBC is especially valuable for improving the classification performance of forest covers having complex forest stand structure and especially useful when higher spatial resolution images are used for land use/cover classification.

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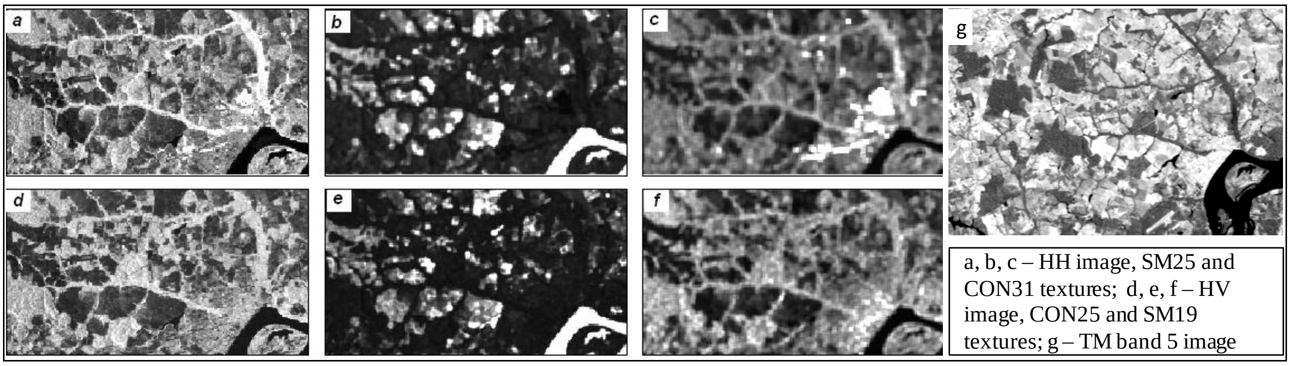

Figure 3. A comparison of ALOS PALSAR L-band HH, HV and derived textural images, as well as Landsat TM band 5 image in the Altamira study area (Note: SM25 and SM19 represent the second moment with a window size of 25x25 pixels and of 19x19 pixels; CON31 and CON25 represent contrast with a window size of 31x31 pixels and of 25x25 pixels)

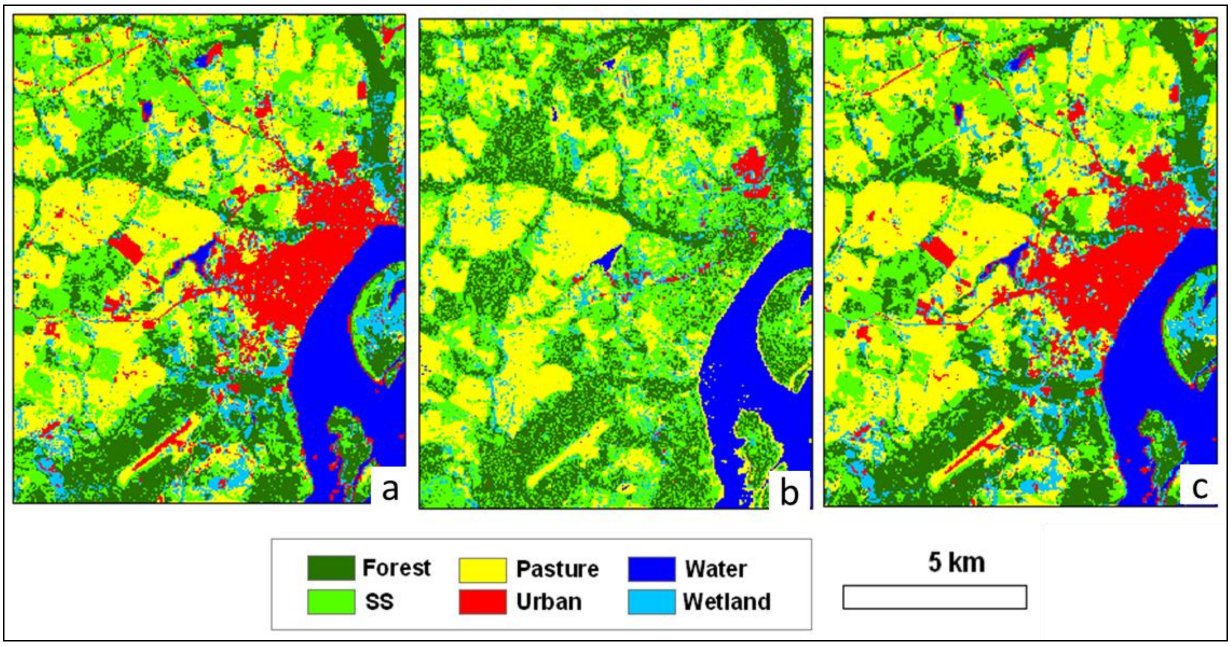

Figure 4. A comparison of classification results with MLC for the Altamira study area from different datasets: (a) Landsat TM image; (b) PALSAR L-band data; (c) TM multispectral and PALSAR L-band HH fusion image with the wavelet-merging technique

Table 1. Comparison of classification results with MLC and OBC on different data scenarios

	Landsat TM image				ALOS PALSAR image				Combination of TM & PALSAR				Fusion of TM & PALSAR			
	MLC		OBC		MLC		OBC		MLC		OBC		MLC		OBC	
	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA
UPF	69.7	88.5	66.7	88.0	51.5	39.5	33.3	44.0	81.8	62.8	69.7	76.7	75.8	89.3	78.8	92.9
FLF	93.3	73.7	86.7	68.4	73.3	61.1	80.0	63.2	86.7	68.4	86.7	76.5	93.3	70.0	93.3	82.4
LIF	83.3	71.4	83.3	71.4	25.0	15.8	58.3	21.2	66.7	88.9	83.3	71.4	91.7	84.6	91.7	84.6
SS1	57.9	57.9	57.9	55.0	42.1	50.0	42.1	53.3	42.1	72.7	36.8	77.8	79.0	71.4	68.4	61.9
SS2	87.5	75.0	91.7	81.5	66.7	64.0	62.5	68.2	87.5	80.8	83.3	76.9	87.5	91.3	87.5	91.3
SS3	85.7	85.7	90.5	86.4	23.8	38.5	28.6	35.3	38.1	80.0	76.2	72.7	90.5	86.4	100.0	84.0
AGP	73.1	82.6	69.2	81.8	76.9	62.5	88.5	67.7	96.2	75.8	96.2	75.8	80.8	91.3	73.1	86.4
WAT	87.5	100.0	95.8	100.0	83.3	95.2	91.7	88.0	87.5	100.0	91.7	100.0	87.5	100.0	91.7	100.0
WET	80.0	92.3	80.0	92.3	33.3	55.6	20.0	75.0	80.0	85.7	86.7	92.9	80.0	100.0	80.0	92.3
URB	100.0	82.1	100.0	85.2	60.9	87.5	60.9	77.8	100.0	88.5	100.0	92.0	100.0	79.3	100.0	82.1
OCA	81.1		81.6		56.1		57.1		78.3		81.1		85.9		85.9	
KAP	0.79		0.80		0.51		0.52		0.76		0.79		0.84		0.84	

Note: MLC and OBC represent maximum likelihood classification and object-based classification; PA and UA represent producer's accuracy and user's accuracy; OCA and KAP represent overall classification accuracy and kappa coefficient. UPF, FLF and LIF represent upland, flooding, and liana forests; SS1, SS2 and SS3 represent initial, intermediate, and advanced succession vegetation stages; AGP, WAT, WET and URB represent agropasture, water, wetland, and urban.