ACT Publication No. 10-01

Land Cover Classification in a Complex Urban-Rural Landscape with QuickBird Imagery

Dengsheng Lu, Scott Hetrick, and Emilio Moran

In: Photogrammetric Engineering & Remote Sensing
Vol. 76, No. 10, October 2010, pp. 1159–1168.

Anthropological Center for Training and Research on Global Environmental Change
Indiana University, Student Building 331, 701 E. Kirkwood Ave., 47405-7100, U.S.A.
Phone: (812) 855-6181, Fax: (812) 855-3000, Email: act@indiana.edu, internet: www.indiana.edu/~act

Land Cover Classification in a Complex Urban-Rural Landscape with QuickBird Imagery

Dengsheng Lu, Scott Hetrick, and Emilio Moran

Abstract

High spatial resolution images have been increasingly used for urban land-use/land-cover classification, but the high spectral variation within the same land-cover, the spectral confusion among different land-covers, and the shadow problem often lead to poor classification performance based on the traditional per-pixel spectral-based classification methods. This paper explores approaches to improve urban land-cover classification with QuickBird imagery. Traditional per-pixel spectral-based supervised classification, incorporation of textural images and multispectral images, spectral-spatial classifier, and segmentation-based classification are examined in a relatively new developing urban landscape, Lucas do Rio Verde in Mato Grosso State, Brazil. This research shows that use of spatial information during the image classification procedure, either through the integrated use of textural and spectral images or through the use of segmentation-based classification method, can significantly improve land-cover classification performance.

Introduction

Landsat images may be the most common data source for land-use/land-cover classification, even in the study of urban landscapes because of the Landsat program's relatively long history of space-based data collection at global scale. However, the relatively coarse spatial resolution often cannot meet specific project requirements of urban land-use/land-cover classification, especially in a complex urban-rural interface (Jensen and Cowen, 1999; Lu and Weng, 2005). In the recent decade, urban researchers have advocated the use of high spatial resolution images (better than 5 m spatial resolution), such as Ikonos and QuickBird, for different applications such as land-use/land-cover classification and impervious surface mapping in urban areas (Sugumaran *et al.*, 2002; Goetz *et al.*, 2003; van der Sande *et al.*, 2003; Xu *et al.*, 2003; Wang *et al.*, 2004; Lu and Weng, 2009). A major advantage of these high spatial resolution images is that such data greatly reduce the mixed-pixel problem (Lu and Weng, 2009), providing a greater potential to extract much more detailed information on land-cover structures than medium or coarse spatial resolution data. However, some new problems associated with the high spatial resolution images emerge, notably the shadows caused by topography, tall buildings, and trees (Asner and Warner, 2003; Zhou *et al.*, 2008; Lu and Weng, 2009), and the high spectral variation within the same land-cover class. These disadvantages may lower classification accuracy if the classification procedure cannot effectively handle them (Irons *et al.*, 1985; Cushnie, 1987). This produces a challenge in selecting suitable classification algorithms and image processing methods.

The heterogeneity in urban landscapes often results in high spectral variation within the same land-cover class in high spatial resolution images. As illustrated in Plate 1 which is a false color composite of QuickBird bands 4, 3, and 2 (assigned as red, green, and blue, respectively) with 0.6 m spatial resolution, the spectral signatures for different kinds of impervious surfaces (appearing as different colors), such as roads, building roofs, and parking lots, vary considerably. Also shadows from tall buildings or from tree crowns significantly reduce the spectral values of the true land-cover under the shadows, resulting in inaccuracies in land-cover classification. When per-pixel spectral-based classifiers are used for land-cover classification, each pixel is individually grouped into a certain category, and the results will be noisy due to high spatial frequency in the landscape. In order to reduce the heterogeneity problem, different methods, such as use of textures in classification and object-oriented classifiers have been examined (Shaban and Dikshit, 2001; Zhang *et al.*, 2003; Walter, 2004; Puissant *et al.*, 2005; Yu *et al.*, 2006; Mathieu *et al.*, 2007; Agüera *et al.*, 2008; Mallinis *et al.*, 2008; Zhou *et al.*, 2008; Pacifici *et al.*, 2009).

Texture often refers to the pattern of variation in intensity in an image. In previous research, many texture measures have been developed (Haralick *et al.*, 1973; He and Wang, 1990; Unser, 1995) and are mainly used for land-use/land-cover classification (Franklin and Peddle, 1989; 1990; Marceau *et al.*, 1990; Augusteijn *et al.*, 1995; Hay *et al.*, 1996; Herold *et al.*, 2003; Yu *et al.*, 2006). For example, Shaban and Dikshit (2001) investigated grey-level co-occurrence matrix, grey-level difference histogram, and sum and difference histogram textures from SPOT spectral data in an Indian urban environment, and found that a combination of texture and spectral features improved the classification accuracy. Compared to the obtained result based solely on spectral features, about 9 percent and 17 percent improvements were achieved using additional one and two textures, respectively. They further

Anthropological Center for Training and Research on Global Environmental Change (ACT), Indiana University, Student Building 331, 701 E. Kirkwood Ave., Bloomington, Indiana, 47405 (dlu@indiana.edu).

Photogrammetric Engineering & Remote Sensing
Vol. 76, No. 10, October 2010, pp. 1159–1168.

0099-1112/10/7610–1159/$3.00/0

Plate 1. Image false color composite consisting of QuickBird bands 4, 3, and 2 by assigning as red, green and blue respectively, showing the complexity of land-use/land-cover features in the high spatial resolution image

found that contrast, entropy, variance, and inverse difference moment provided higher accuracy and that the best sizes of moving window were 7 × 7 and 9 × 9. In practice, it is often difficult to identify a suitable texture because texture varies with the characteristics of the landscape under investigation and the image data used. Identification of suitable textures involves the determination of a texture measure, image band, the size of moving window, and other parameters (Franklin *et al*., 1996; Chen *et al*., 2004). The difficulty in identifying suitable textures and the computation cost for calculating textures limit extensive use of textures in image classification.

Because per-pixel spectral-based methods cannot effectively solve the high spectral variation problem within the same land-cover, object-oriented classification methods have been regarded as a good choice to reduce this problem (Thomas *et al.*, 2003; Benz *et al*., 2004; Laliberte *et al*., 2004; Jensen, 2004; Yu *et al*., 2006; Mathieu *et al*., 2007; Stow *et al*., 2007; Jacquin *et al*., 2008; Mallinis *et al*., 2008; Zhou *et al*., 2008). Two stages are involved in an object-oriented classification: image segmentation and classification (Jensen, 2004). Image segmentation merges pixels into objects, and a classification is then implemented based on those objects instead of the individual pixels. In the process of creating objects, scale determines the occurrence or absence of an object class, and the size of an object affects a classification result (Jensen, 2004). This approach has proven to be able to provide better classification results than per-pixel classification approaches, especially for high spatial resolution data (Thomas *et al*., 2003; Laliberte *et al*., 2004; Wang *et al*., 2004; Mallinis *et al*., 2008). The eCognition® (renamed as Definiens) method is so far the most commonly used object-oriented classification (Benz *et al*., 2004, Wang *et al*., 2004; Yu *et al*., 2006; Jacquin *et al*., 2008).

In order to improve land-cover classification with high spatial resolution images, one critical issue is to make use of spatial information inherent in high spatial resolution images while reducing the high spectral variation within the same land-cover class. The incorporation of texture and spectral bands, and the use of object-oriented classification methods have been explored (Yu *et al*., 2006). However, how to effectively use spatial information is still poorly understood. It is valuable to conduct a comparative analysis of different methods in order to identify a suitable method for urban land-cover classification. Therefore, this research selected a complex urban-rural frontier, i.e., Lucas do Rio Verde in Mato Grosso State, Brazil, as a case study and used QuickBird imagery to explore the integrated use of textural and spectral images, the spectral-spatial classifier, and the segmentation-based method, in order to identify a suitable classification procedure for urban land-cover classification.

A Brief Introduction of Selected Classification Methods

Maximum Likelihood Classifier

Maximum likelihood classifier (MLC) is a parametric classifier that assumes normal or near normal spectral distribution for each feature of interest. An equal prior probability among the classes is also assumed. This classifier is based on the probability that a pixel belongs to a particular class. It takes the variability of classes into account by using the covariance matrix. Therefore, MLC requires sufficient number of representative training samples for each class to accurately estimate the mean vector and covariance matrix needed by the classification algorithm (Hubert-Moy *et al.*, 2001; Chen and Stow, 2002; Landgrebe, 2003; Mather, 2004). When the training samples are limited or non-representative, inaccurate estimation of the mean vector and covariance matrix often results in poor classification results. A detailed description of MLC can be found in many textbooks (e.g., Richards and Jia, 1999; Lillesand and Kiefer, 2000; Jensen, 2004). MLC may be the most common classifier used in practice because of its sound theory and its ubiquitous nature in commercial image processing software.

ECHO

Extraction and Classification of Homogeneous Objects (ECHO) is a multistage spectral-spatial classifier that combines spectral and spatial/textural features (Kettig and Landgrebe, 1976; Landgrebe, 1980; Biehl and Landgrebe, 2002). Four stages are involved during the classification: (a) an analyst defines partitions within the feature space (2×2, 3×3, 4×4, etc.) that creates multipixel cells; (b) an analyst sets thresholds to determine the homogeneity of pixels within each cell. After processing, each cell is then either considered a single multipixel entity where individual pixel spectral statistics are merged or they function as individual pixels just located within a cell's coordinates; (c) full cells and individual pixels within some cells are aggregated based on spectral statistical associations between them; and (d) the aggregations of cells of pixels and single pixels are processed by a MLC to provide the final results. Our previous research for land-cover classification in the Brazilian Amazon based on Landsat TM images has shown that ECHO can provide better classification accuracy than MLC (Mausel *et al.*, 1993; Lu *et al.*, 2004). This research used ECHO to classify QuickBird imagery in a complex urban-rural frontier.

Segmentation-based Classification

Image segmentation is the partitioning of raster images into spatially continuous, disjointed, and homogeneous regions, i.e., segments, based on pixel values and locations (Blashke *et al.*, 2004; Jensen, 2004). The pixels having similar spectral values that are spatially connected are grouped in a single segment. One critical step in this method is to develop a segmentation image, which is often based on pixel, edge, and region methods (Blaschke *et al.*, 2004; Yu *et al.*, 2006). In this research, the edge-based segmentation method is used to produce segmentation images based on QuickBird multispectral images. The major steps include: (a) producing segmentation image from the QuickBird multispectral image using SEGMENTATION function in the ERDAS Imagine®; (b) converting the segmentation image into vector format image and removing the segments with small areas using ArcGIS®; (c) extracting the mean spectral value of each segment for each band; (d) conducting supervised classification for the mean-spectral value image; (e) recoding the classified image according to the selected classification scheme; and (f) conducting accuracy assessment.

Study Area and Data Set

Brief Description of the Study Area

Lucas do Rio Verde (hereafter called simply Lucas) in Mato Grosso State, Brazil has a relatively short history and small urban extent. It was established in the early 1980s (see Figure 1) and has experienced a rapid urbanization. Highway BR-163 runs through Lucas and connects the region to

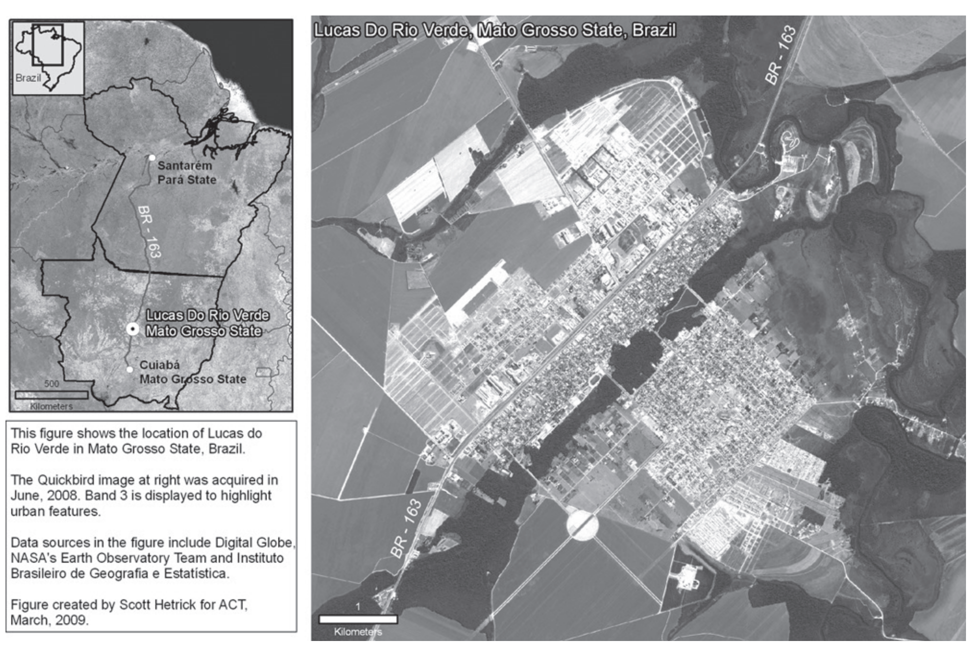

Figure 1. Study area: Lucas do Rio Verde, Mato Grosso State, Brazil.

the Amazon River port city of Santarém and to the heart of the soybean growing area at Cuiabá. The economic base of Lucas is large-scale agriculture, including the production of soy, cotton, rice, and corn as well as poultry and swine. The county is at the epicenter of soybean production in Brazil, and it is expected to grow in population three-fold in the next ten years (personal communication with secretariat for planning at Lucas). Because it is, at present, a relatively yet small town and has complex urban-rural spatial patterns derived from its highly capitalized agricultural base, large silos and warehouses, and planned urban growth, Lucas is an ideal site to explore the methods to classify a high spatial resolution image into a thematic map.

Data Set

A QuickBird image, which was acquired on 20 June 2008, was used in this research for exploring the suitable methods for land-use/land-cover classification. The QuickBird imagery has four multispectral bands (blue, green, red, and near-infrared) with 2.4 m spatial resolution and one panchromatic band (visible wavelength) with 0.6 m spatial resolution. In order to make full use of both multispectral and high spatial resolution features inherent in the remotely sensed data, different data fusion methods such as intensity-hue-saturation (IHS) transform, principal component analysis (PCA), and wavelet transform can be used (Welch and Ehlers, 1987; Solberg *et al.*, 1996; Pohl and Van Genderen, 1998; Amolins *et al.*, 2007; Dong *et al.*, 2009). In particular, the wavelet merging technique is regarded as a good method for preserving the multispectral features while improving the spatial features in the output result (Li *et al.*, 2002; Ulfarsson *et al.*, 2003; Lu *et al.*, 2008). Hence, the wavelet merging technique was used in this research to merge the QuickBird multispectral bands and panchromatic band into a new multispectral image with 0.6 m spatial resolution. The fused image was then used to examine suitable methods for land-use/land-cover classification in a complex urban-rural frontier.

Methods

Determination of a Classification System and Selection of Training Sample Plots

A suitable classification scheme is required before implementing a land-cover classification. Many factors may affect the determination of a classification scheme, but the major concerns are research objectives, user's needs, characteristics of the study area, and selected remote sensing data (Lu and Weng, 2007). In this research, the selected classification system includes the following land-use/land-cover classes: forest, impervious surfaces, pasture/grassland, water, wetland, bare soil, and cropped fields (i.e., harvested fields with crop residues).

In this study area, impervious surfaces are extremely complex, as shown in Plate 1. Different impervious surfaces such as building roofs, roads, and parking lots have different spectral signatures, and are confused with other land-covers such as bare soils, water, wetland, and crop residuals due to their similar spectral signatures. Another important factor that affects land-cover classification performance is the shadow problem, i.e., shadows cast by buildings and tree crowns, reducing the spectral values of the true land-cover under the shadows. Therefore, proper selection of training sample plots is critical for the land-cover classification. Since impervious surfaces have large spectral variation, no single class can represent all impervious surface materials. Thus, different impervious surface training sample classes were selected, representing low-, medium-, and high-spectral-value impervious surfaces, dirty roads, parking lots, and shadowed impervious surface. Other land-covers include upland forest, riverine forest, agroforestry, grassland/pasture, bare soils, shadows in vegetated areas, cropped fields, water, and non-forest wetlands. At least 15 sample plots for each training class were selected, based on visual interpretation on the QuickBird false color composite. A transformed divergence algorithm was used to examine the separability of the land-cover classes and then to further refine the selected training samples. The same training samples were used for the different classification methods investigated here.

Selection of Suitable Textural Images

Many texture measures are available, but it is a challenge to identify suitable textural images for a specific study area, because a good texture is a comprehensive combination of a texture measure, window size, image band, quantization level, and the inter-pixel distance (Shaban and Dikshit, 2001; Lu and Weng, 2007; Pacifici *et al.*, 2009), and is also related to characteristics of the landscape under investigation. In practice, grey-level co-occurrence matrix (GLCM) based texture measures are often used (Yu *et al.*, 2006; Agüera *et al.*, 2008). Based on literature review and our previous experiences (Lu and Weng, 2005 and 2007), four GLCM-based texture measures (i.e., mean, homogeneity, dissimilarity, and second moment) with three different window sizes (9×9, 15×15, and 21×21) were tested, based on the QuickBird red and near-infrared (NIR) bands. The same training samples were used to examine which textural image or images had better separability based on the transformed divergence analysis. The textural images having best separability performance were then incorporated into multispectral images for land-cover classification.

Development of Segmentation-based Mean Spectral Value Images

In the QuickBird images, there exists high data redundancy between visible bands such as between bands 1 and 2 (the correlation coefficient is 0.98) in this study. Because of the large volume data sets in the QuickBird images and the time required for image processing, band 1 was not used during the extraction of the segmentation image. In this research, the segmentation function provided by ERDAS Imagine® was used to produce segmentation image. During the production of the segmentation image, it is important to identify suitable thresholds for edge detection and for the determination of the difference between neighboring segments. Therefore, different thresholds ranging from 20, 30, 40, 50, until 60 for edge detection and different parameter values of the minimum value difference ranging from 15, 25, 30, to 40 for determining whether the pixels belonged to the same segment or not were examined for the 16-bit integer format QuickBird images. Based on the examination of segmentation images, an edge detection threshold of 50 and the minimum value difference of 30 were finally used in this research. The segmentation image was converted to vector format and those segments with very small areas were merged to the neighbor segment. The modified segmentation image was then linked to QuickBird spectral bands to extract a mean spectral value for each segment in each band separately.

Implementation of the Land-use/Land-cover Classification

The same training samples were used for land-cover classification with different methods. The following four classification strategies were designed: (a) MLC based on QuickBird bands 2, 3, and 4 images; (b) MLC based on the combination of QuickBird band 2, 3, and 4 and two textural images; (c) ECHO based on QuickBird bands 2, 3, and 4 images; and (d) MLC based on segmentation-based mean-spectral value images of bands 2, 3, and 4. After classification, the land-cover classes were then recoded according to the selected classification scheme.

Accuracy Assessment

Accuracy assessment is often required for evaluating the quality of land-cover classification results or for identifying a suitable classification method by comparing different classification results in a study area. The error matrix approach is most frequently used in accuracy assessment (Foody, 2002). Other important accuracy assessment elements, such as overall classification accuracy (OCA), producer's accuracy (PA), user's accuracy (UA), and kappa coefficient (KC), can be derived from the error matrix. Previous literature has defined the meanings and provided computation methods for these elements (Congalton and Mead, 1983; Hudson and Ramm, 1987; Congalton, 1991; Janssen and van der Wel, 1994; Congalton and Plourde, 2002; Foody, 2002; Congalton and Green, 2008). In this research, a total of 300 test samples were randomly selected. The analyst examined the test sample plots and assigned a class value to each. The accuracy assessment was conducted for each classification result.

Results

Selection of Suitable Textural Images

The transformed divergence analysis based on training samples indicated that use of two textural images provided sufficiently good separability. Adding more textural images did not significantly improve the land-cover separability (Shaban and Dikshit, 2001; Lu *et al.*, 2008), but did increase the data volume because of the high spatial resolution. Window size is an important factor affecting the role of textural images in land-cover classification. Too large a window size requires much more time for computation and also smoothes the textural images thereby reducing the separability of boundaries. As shown in Figure 2, the textural image with a large window size of the same texture measure from red-band image over-extracted impervious surface classes, especially the linear features (see Figure 2c and 2d). Based on the analysis of transformed divergence, two textural images based on mean and dissimilarity with a window size of 9×9 pixels on the QuickBird red-band image were finally selected. The low correlation coefficient between mean and dissimilarity textural images indicates that they have low data redundancy and have high complementary information, thus, both textural images were incorporated into multispectral image for land-cover classification.

Comparison of the Different Classification Methods

The role of textural images in improving land-use/land-cover classification accuracy is obvious, as shown in Table 1. The addition of textural images improved the accuracy of each land-cover class, especially wetland, bare soil, and cropped fields. Comparing the result from the combination of spectral and textural images with that from the pure spectral images, overall classification accuracy was improved by 11.7 percent

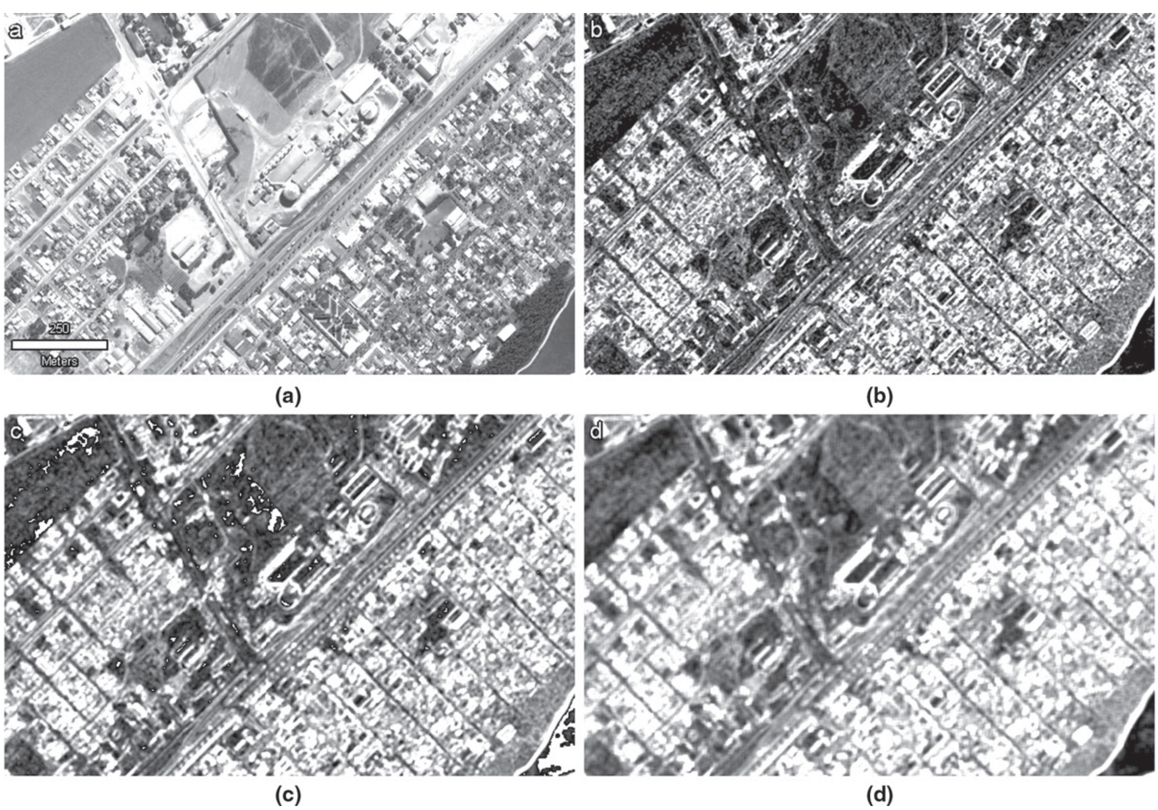

Figure 2. Comparison of textural images: (a) red-band image, (b), (c), and (d) textural images derived with dissimilarity texture measure on the red-band images with three window sizes of 9×9, 15×15, and 21×21 pixels, respectively.

Table 1. A Comparison of Accuracy Assessment Results among Different Methods

Land-cover	Maximum likelihood classifier						ECHO			Segmentation-based Method		
	Spectral Image			Spectral and Texture								
	PA	UA	KC	PA	UA	KC	PA	UA	KC	PA	UA	KC
Forest	92.45	71.01	0.65	95.08	89.23	0.86	87.50	87.50	0.85	90.57	90.31	0.89
ImpS	95.12	76.47	0.73	90.91	85.11	0.83	77.78	81.40	0.78	87.80	92.31	0.91
Pas-Gra	75.00	62.26	0.56	74.47	77.78	0.74	74.36	67.44	0.63	75.00	71.74	0.67
Water	70.97	100.00	1.00	80.00	100.00	1.00	90.32	93.33	0.93	96.77	100.00	1.00
Wetland	31.03	52.94	0.48	88.89	72.73	0.71	96.30	76.47	0.74	100.00	82.86	0.81
Bare	69.70	82.14	0.80	87.10	93.10	0.92	85.00	53.13	0.50	93.94	86.11	0.84
Fields	75.36	86.67	0.83	89.86	91.18	0.89	74.39	98.39	0.98	84.06	95.08	0.94
OCA		75.67			87.33			81.67			88.33	
OKC		0.71			0.85			0.78			0.86	

Note: PA, UA, and KC represent producer's accuracy, user's accuracy, and kappa coefficient for each land-cover class; OCA and OKC represent overall classification accuracy and overall kappa coefficient. ImpS and Pas-Gra represent impervious surfaces and pasture/grass land

and overall kappa coefficient by 0.14. In the classification result from the MLC based on per-pixel spectral signatures, major land-cover misclassification errors involved spectral confusion among wetland, dark impervious surfaces, and shadows from buildings or from tree crowns, and among pasture/grassland, cropped fields, bare soils, and impervious surfaces. As an example, Figure 3 shows the complexity of impervious surfaces and the spectral similarity with water, wetland, and shadows indicating the difficulty in separating them based on spectral signatures. Therefore, per-pixel spectral-based supervised classification cannot effectively separate these land-covers based on pure spectral signatures alone. However, different land-cover classes have their own spatial patterns and characteristics. In particular, high spatial resolution images have rich spatial information that can be used for classification. As Table 1 indicated, texture is an effective method to generate a new data set by extracting spatial information in the new image. Another method is to use the spatial information by incorporating the spectral and spatial information in a classifier such as ECHO, as used in this paper. Comparing the MLC-based classification result, the ECHO improved overall land-cover classification accuracy by 6 percent.

Comparing the classification accuracies between using segmentation-based mean-spectral images and using per-pixel spectral-based multispectral images indicated that segmentation-based method significantly improved classification performance for all land-covers. Overall classification accuracy was increased by 12.7 percent and the kappa coefficient by 0.15. This implies that reducing spectral variation within the same land-cover through using segmentation is valuable. Figure 4 shows the comparison of segmentation-based mean-spectral red-band image and corresponding original red-band image, showing the homogenous features within the same land-cover. Analyzing the classification images (see Plate 2) indicated that MLC based on multispectral images gave a large number of "salt-and-pepper" outputs and had many misclassifications, but the other three methods significantly reduced this problem. In particular, the use of texture and segmentation provided the best classification performance. This implies that use of spatial information, either through the incorporation of textural and spectral images, segmentation, or a spatial-spectral classifier, can improve land-cover classification performance.

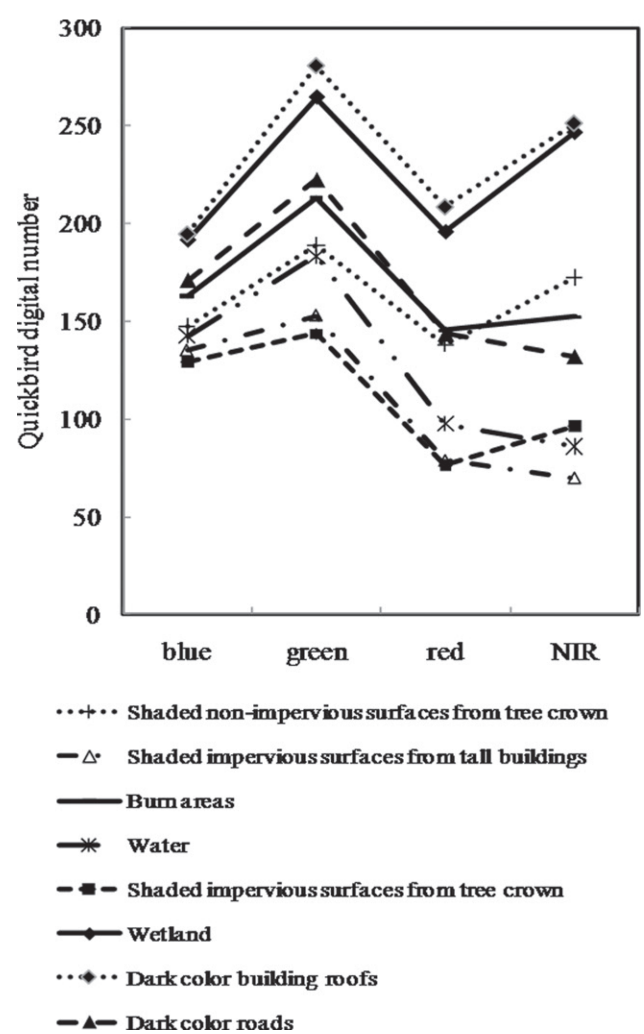

Figure 3. A comparison of spectral signatures among low reflectance objects, illustrating the difficulty in separating land-cover classes based on spectral signatures.

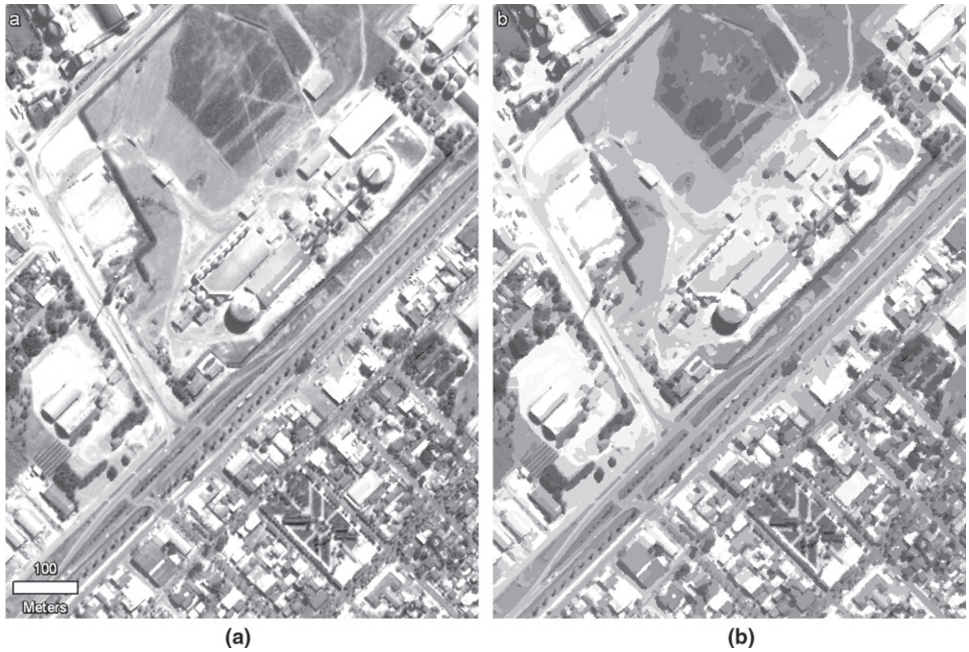

Figure 4. Comparison of (a) original red-band image, and (b) segmentation-based mean-spectral red-band image.

Discussion

The high spatial resolution in the QuickBird image often lead to high spectral variation within the same land-cover class, and the limited number of spectral bands, including the lack of a shortwave infrared band, leads to a high rate of spectral confusion, resulting in poor classification performance based on per-pixel spectral-based classification methods. Reducing the spectral variation within the same land-covers and increasing the separability of different land-covers are the keys to improving land-cover classification (Lu and Weng, 2007). As this research indicates, the use of texture, segmentation, or a spectral-spatial classifier are effective methods for improving land-cover classification performance when high spatial resolution images are used in a complex urban landscape. Texture not only reduces the spectral variation within the same land-cover but also improves the spectral separability among different land-covers, thus incorporation of texture is an effective way to improve classification performance (Agüera *et al.*, 2008; Lu *et al.*, 2008). The difficulty is to identify suitable textures because a good texture is dependent on the proper determination of the texture measure, image band, and window size for the specific study (Chen *et al.*, 2004). There are so many potential textures available, it is important to use suitable rules to conduct the texture selection (Lu and Weng, 2007; Lu *et al.*, 2008). In this research, the selection of textural images is based on the separability analysis with the transformed divergence on the training samples and has shown its success in improving land-use/land-cover classification accuracy.

In addition to the use of textural images, selection of suitable classification methods can also improve classification performance (Lu *et al.*, 2004). In the high spatial resolution images, one important factor to improve land-cover classification performance is to reduce the spatial variation within the same land-covers. Traditional per-pixel spectral-based supervised classification is only based on spectral signatures, but does not make use of rich spatial information inherent in the high spatial resolution images. This research has shown that the use of spatial information in the classifier, either in ECHO or segmentation-based method is an effective way to improve land-cover classification performance. One critical issue is to develop a high-quality segmentation image, depending on the use of method for segmentation development and the selection of relevant parameters (Yu *et al.*, 2006; Lu and Weng, 2007; Mallinis *et al.*, 2008). The selection of the thresholds seems subjective; mainly depending on the analyst's experience, the data range, and the characteristics of land-covers in the study area. Also no thresholds are optimal for all different land-covers due to the complexity of the urban landscapes under investigation. More research is needed to identify suitable parameter inputs for developing segmentation images corresponding to the different complexity of urban landscapes.

Shadow is another important factor reducing the spectral values of the shaded objects or even total loss of spectral information, thus influencing the land-cover classification with digital image processing (Lu and Weng, 2009; Zhou *et al.*, 2009). In high spatial resolution images such as QuickBird, shadow problem is especially serious as shown in Plate 1. This impact varies, depending on the shadowing degree (Lu and Weng, 2009). Although much research has been conducted to explore the methods for shadow detection and removal (Dare, 2005; Li *et al.*, 2005; Lu, 2007; Lu and Weng, 2009; Zhou *et al.*, 2009), it is hard to eliminate the shadow impacts on land-cover classification. To date, there are no existing suitable techniques that can automatically eliminate the shadow impacts. An easy and simple method is to identify thresholds to mask out the pixels under shadow impacts, then classify the spectral signatures of the shadowed pixels into clusters and the analyst can make full use of his/her experience and knowledge to merge the clusters into meaningful land-cover

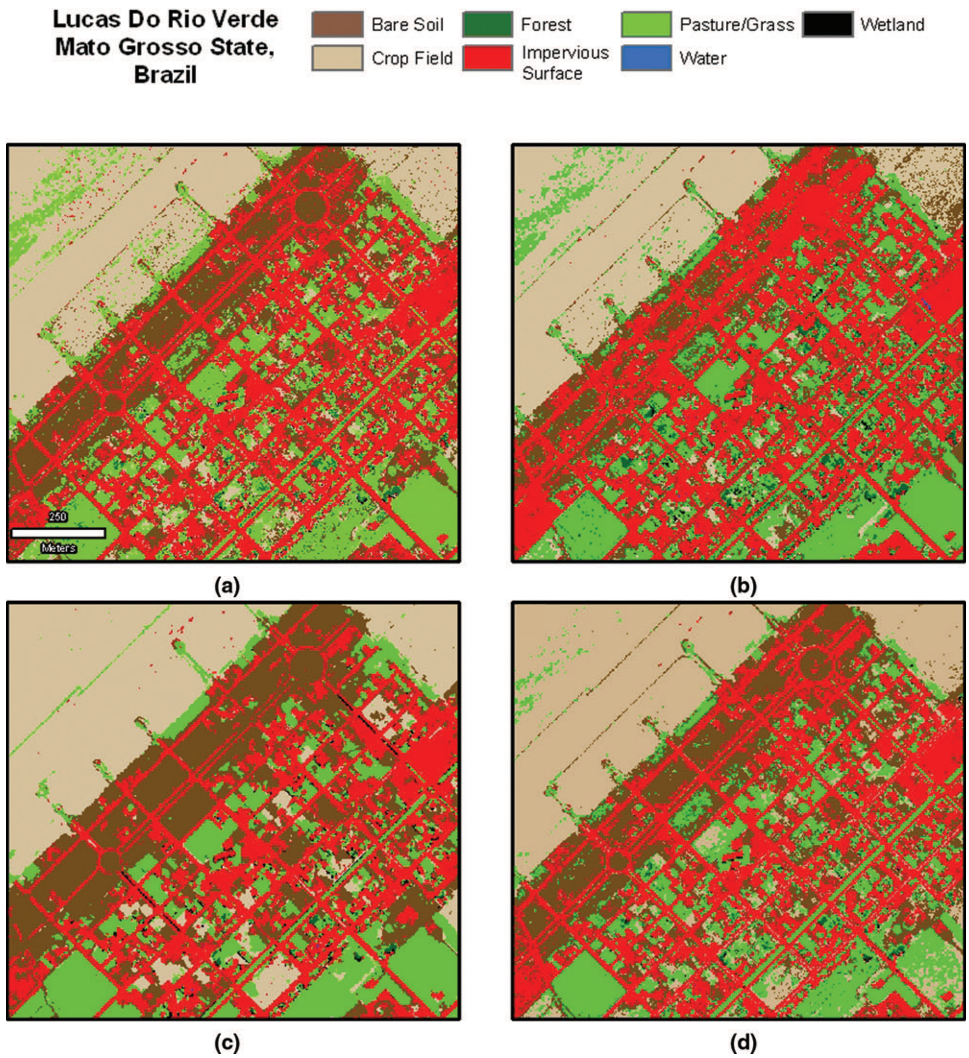

Plate 2. A comparison of classified images from different classification methods: (a) MLC based on multispectral image, (b) ECHO based on multispectral image, (c) segmentation-based method, and (d) combination of multispectral and textural images)

classes (Lu and Weng, 2009). Human beings can comprehensively use their knowledge and experience to separate different land-covers in the shadowed areas in the high spatial resolution images.

Selecting different seasonal images is helpful in separating some types of land-cover classes, for example, pasture/grassland, bare soils, and cropped fields. On the QuickBird image which was acquired on 20 June 2008, cropped fields were often confused with impervious surfaces because crops were harvested and crop residues remained in the fields. We used another image, acquired on 02 April 2007, when crops were still in the fields. Growing crops and impervious surfaces have significantly different spectral signatures in the growing season, thus they can be easily separated from the different spectral signatures. Therefore, selection of a suitable acquisition date or the use of different phenological images is valuable for further improving land-cover classification accuracy (Sugumaran *et al*., 2002). However, because of high spatial resolution, use of multi-temporal QuickBird images will greatly increase the time and labor to conduct the image processing, in addition to the cost increase in image purchase.

Conclusions

The high spectral variation within the same land-cover, the spectral confusion of different land-covers due to limited spectral bands and lack of shortwave infrared bands, and shadow impacts in the QuickBird image make it difficult in land-cover classification with computer-based automatic processing methods. Traditional per-pixel spectral-based supervised classification cannot effectively deal with these problems, thus the classification results are often unsatisfactory. This research indicates that making full use of spatial information is important to improve land-cover classification performance. Incorporation of suitable textural and spectral images or the use of segmentation-based classification methods can significantly improve land-cover classification comparing with traditional per-pixel spectral-based classification methods.

Acknowledgments

The authors wish to thank the National Institute of Child Health and Human Development at NIH (Grant No. R01 HD035811) for the funds that made this study possible. The study is part of a five-year continuation project focusing on Population and Environment, which includes examining changes taking place in urban areas. Any errors are solely the responsibility of the authors and not of the funding agencies.

References

Asner, G.P., and A.S. Warner, 2003. Canopy shadow in IKONOS satellite observations of tropical forests and savannas, *Remote Sensing of Environment*, 87:521–533.

Agüera, F., F.J. Aguilar, and M.A. Aguilar, 2008. Using texture analysis to improve per-pixel classification of very high resolution images for mapping plastic greenhouses, *ISPRS Journal of Photogrammetry and Remote Sensing*, 63:635–646.

Amolins, K., Y. Zhang, and P. Dare, 2007. Wavelet based image fusion techniques - An introduction, review and comparison, *ISPRS Journal of Photogrammetry and Remote Sensing*, 62:249–263.

Augusteijn, M.F., L.E. Clemens, and K.A. Shaw, 1995. Performance evaluation of texture measures for ground cover identification in satellite images by means of a neural network classifier, *IEEE Transactions on Geoscience and Remote Sensing*, 33:616–625.

Benz, U.C., P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen, 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information, *ISPRS Journal of Photogrammetry and Remote Sensing*, 58:239–258.

Biehl, L., and D. Landgrebe, 2002. MultiSpec - A tool for multi-spectral-hyperspectral image data analysis, *Computers and Geosciences*, 28:1153–1159.

Blaschke, T., C. Burnett, and A. Pekkarinen, 2004. Image segmentation methods for object-based analysis and classification, *Remote Sensing Image Analysis: Including the Spatial Domain* (S.M. de Jong and F.D. van der Meer, editors), Kluwer Academic Publishers, Netherlands, pp. 211–236.

Chen, D., and D.A. Stow, 2002. The effect of training strategies on supervised classification at different spatial resolution, *Photogrammetric Engineering & Remote Sensing*, 68(11):1155–1162.

Chen, D., D.A. Stow, and P. Gong, 2004. Examining the effect of spatial resolution and texture window size on classification accuracy: an urban environment case, *International Journal of Remote Sensing*, 25:2177–2192.

Congalton, R.G., 1991. A review of assessing the accuracy of classification of remotely sensed data, *Remote Sensing of Environment*, 37:35–46.

Congalton, R.G., and R.A. Mead, 1983. A quantitative method to test for consistency and correctness in photo interpretation, *Photogrammetric Engineering & Remote Sensing*, 49(1):69–74.

Congalton, R.G., and L. Plourde, 2002. Quality assurance and accuracy assessment of information derived from remotely sensed data, *Manual of Geospatial Science and Technology* (J. Bossler, editor), Taylor & Francis, London, pp. 349–361.

Congalton, R.G., and K. Green, 2008. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*, Second edition, CRC Press, Taylor & Francis Group, Boca Raton, Florida, ISBN 978-1-4200-5512-2, 183 p.

Cushnie, J.L., 1987. The interactive effect of spatial resolution and degree of internal variability within land-cover types on classification accuracies, *International Journal of Remote Sensing*, 8:15–29.

Dare, P.M., 2005. Shadow analysis in high-resolution satellite imagery of urban areas, *Photogrammetric Engineering & Remote Sensing*, 71(2):169–177.

Dong, J., D. Zhuang, Y. Huang, and J. Yu, 2009. Advances in multi-sensor data fusion: algorithms and applications, *Sensor*, 9:7771–7784.

Foody, G.M., 2002. Status of land-cover classification accuracy assessment, *Remote Sensing of Environment*, 80:185–201.

Franklin, S.E., and D.R. Peddle, 1989. Spectral texture for improved class discrimination in complex terrain, *International Journal of Remote Sensing*, 10:1437–1443.

Franklin, S.E., and D.R. Peddle, 1990. Classification of SPOT HRV imagery and texture features, *International Journal of Remote Sensing*, 11:551–556.

Franklin, S.E., M.A. Wulder, and M.B. Lavigne, 1996. Automated derivation of geographic window sizes for remote sensing digital image texture analysis, *Computers and Geosciences*, 22:665–673.

Goetz, S.J., R.K. Wright, A.J. Smith, E. Zinecker, and E. Schaub, 2003. IKONOS imagery for resource management: Tree cover, impervious surfaces, and riparian buffer analyses in the mid-Atlantic region, *Remote Sensing of Environment*, 88:195–208.

Haralick, R.M., K. Shanmugam, and I. Dinstein, 1973. Textural features for image classification, *IEEE Transactions on Systems, Man and Cybernetics*, SMC-3:610–620.

Hay, G.J., K.O. Niemann, and G.F. McLean, 1996. An object-specific image-texture analysis of H-resolution forest imagery, *Remote Sensing of Environment*, 55:108–122.

He, D.C., and L. Wang, 1990. Texture unit, textural spectrum and texture analysis, *IEEE Transaction on Geoscience and Remote Sensing*, 28:509–512.

Herold, M., X. Liu, and K.C. Clarke, 2003. Spatial metrics and image texture for mapping urban land-use, *Photogrammetric Engineering & Remote Sensing*, 69(9):991–1001.

Hubert-Moy, L., A. Cotonnec, L. Du, A. Chardin, and P. Perez, 2001. A comparison of parametric classification procedures of remotely sensed data applied on different landscape units, *Remote Sensing of Environment*, 75:174–187.

Hudson, W.D., and C.W. Ramm, 1987. Correct formulation of the Kappa coefficient of agreement, Photogrammetric Engineering & Remote Sensing, 53(4):421–422.

Irons, J.R., B.L. Markham, R.F. Nelson, D.L. Toll, D.L. Williams, R.S. Latty, and M.L. Stauffer, 1985. The effects of spatial resolution on the classification of Thematic Mapper data, *International Journal of Remote Sensing*, 6:1385–1403.

Jacquin, A., L. Misakova, and M. Gay, 2008. A hybrid object-based classification approach for mapping urban sprawl in periurban environment, *Landscape and Urban Planning*, 84:152–165.

Janssen, L.F.J., and F.J.M. van der Wel, 1994. Accuracy assessment of satellite derived land-cover data: A review, *Photogrammetric Engineering & Remote Sensing*, 60(4): 419–426.

Jensen, J.R., and D.C. Cowen, 1999. Remote sensing of urban/suburban infrastructure and socioeconomic attributes, *Photogrammetric Engineering & Remote Sensing*, 65(6):611–622.

Jensen, J.R., 2004. *Introductory Digital Image Processing: A Remote Sensing Perspective*, Third edition, Prentice Hall, Upper Saddle River, New Jersey., 526 p.

Kettig, R.L., and D.A. Landgrebe, 1976. Computer classification of remotely sensed multispectral image data by extraction and classification of homogeneous objects, *IEEE Transactions on Geoscience Electronics*, GE-14:19–26.

Laliberte, A.S., A. Rango, K.M. Havstad, J.F. Paris, R.F. Beck, R. McNeely, and A.L. Gonzalez, 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico, *Remote Sensing of Environment*, 93:198–210.

Landgrebe, D.A., 1980. The development of a spectral-spatial classifier for Earth observational data, *Pattern Recognition*, 12:165–175.

Landgrebe, D.A., 2003. *Signal Theory Methods in Multispectral Remote Sensing*, John Wiley & Sons, Hoboken, New Jersey, 508p.

Li, S., J.T. Kwok, and Y. Wang, 2002. Using the discrete wavelet frame transform to merge Landsat TM and SPOT panchromatic images, *Information Fusion*, 3:17–23.

Li, Y., P. Gong, and T. Sasagawa, 2005. Integrated shadow removal based on photogrammetry and image analysis, *International Journal of Remote Sensing*, 26(18):3911–3929.

Lillesand, T.M., and R.W. Kiefer, 2000. *Remote Sensing and Image Interpretation*, Fourth edition, John Wiley & Sons, New York, 724 p.

Lu, D., 2007. Detection and substitution of clouds/hazes and their cast shadows on IKONOS images, *International Journal of Remote Sensing*, 28(18):4027–4035.

Lu, D., P. Mausel, M. Batistella, and E. Moran, 2004. Comparison of land-cover classification methods in the Brazilian Amazon basin, *Photogrammetric Engineering & Remote Sensing*, 70(7):723–731.

Lu, D., and Q. Weng, 2005. Urban classification using full spectral information of Landsat ETM+ imagery in Marion County, Indiana, *Photogrammetric Engineering & Remote Sensing*, 71(12):1275–1284.

Lu, D., and Q. Weng, 2007. A survey of image classification methods and techniques for improving classification performance, *International Journal of Remote Sensing*, 28(5):823–870.

Lu, D., M. Batistella, E. Moran, and E.E. de Miranda, 2008. A comparative study of Landsat TM and SPOT HRG images for vegetation classification in the Brazilian Amazon, *Photogrammetric Engineering & Remote Sensing*, 70(3):311–321.

Lu, D., and Q. Weng, 2009. Extraction of urban impervious surface from an IKONOS image, *International Journal of Remote Sensing*, 30(5):1297–1311.

Mallinis, G., N. Koutsias, M. Tsakiri-Strati, and M. Karteris, 2008. Object-based classification using QuickBird imagery for delineating forest vegetation polygons in a Mediterranean test site, *ISPRS Journal of Photogrammetry and Remote Sensing*, 63:237–250.

Marceau, D.J., P.J. Howarth, J.M. Dubois, and D.J. Gratton, 1990. Evaluation of the grey-level co-occurrence matrix method for land-cover classification using SPOT imagery, *IEEE Transactions on Geoscience and Remote Sensing*, 28:513–519.

Mather, P.M., 2004. *Computer Processing of Remotely-Sensed Images: An Introduction*, Third edition, John Wiley & Sons Ltd, Chichester, U.K., 339 p.

Mathieu, R., J. Aryal, and A.K. Chong, 2007. Object-based classification of IKONOS imagery for mapping large-scale vegetation communities in urban areas, *Sensors*, 7:2860–2880.

Mausel, P., Y. Wu, Y. Li, E.F. Moran, and E.S. Brondízio, 1993. Spectral identification of succession stages following deforestation in the Amazon, *Geocarto International*, 8:61–72.

Pacifici, F., M. Chini, and W.J. Emery, 2009. A new network approach using multi-scale textural metrics from very high-resolution panchromatic imagery for urban land-use classification, *Remote Sensing of Environment*, 113:1276–1292.

Pohl, C., and J.L. van Genderen, 1998. Multisensor image fusion in remote sensing: concepts, methods, and applications, *International Journal of Remote Sensing*, 19:823–854.

Puissant, A., J. Hirsch, and C. Weber, 2005. The utility of texture analysis to improve per-pixel classification for high to very high spatial resolution imagery, *International Journal of remote Sensing*, 26:733–745.

Richards, J.A., and X. Jia, 1999. *Remote Sensing Digital Image Analysis: An Introduction*, Third edition, Springer-Verlag, Berlin, Germany, 363 p.

Shaban, M.A., and O. Dikshit, 2001. Improvement of classification in urban areas by the use of textural features: The case study of Lucknow city, Uttar Pradesh, *International Journal of Remote Sensing*, 22: 565–593.

Solberg, A.H.S., T. Taxt, and A.K. Jain, 1996. A Markov random field model for classification of multisource satellite imagery, *IEEE Transactions on Geoscience and Remote Sensing*, 34:100–112.

Stow, D., A. Lopez, C. Lippitt, S. Hinton, and J. Weeks, 2007. Object-based classification of residential land-use within Accra, Ghana based on QuickBird satellite data, *International Journal of Remote Sensing*, 28:5167–5173.

Sugumaran, R., D. Zerr, and T. Prato, 2002. Improved urban land-cover mapping using multitemporal IKONOS images for local government planning, *Canadian Journal of Remote Sensing*, 28: 90–95.

Thomas, N., C. Hendrix, and R.G. Congalton, 2003. A comparison of urban mapping methods using high-resolution digital imagery, *Photogrammetric Engineering & Remote Sensing*, 69(9): 963–972.

Ulfarsson, M.O., J.A. Benediktsson, and J.R. Sveinsson, 2003. Data fusion and feature extraction in the wavelet domain, *International Journal of Remote Sensing*, 24:3933–3945.

Unser, M., 1995. Texture classification and segmentation using wavelet frames, *IEEE Transactions on Image Processing*, 4:1549–1560.

Van der Sande, C.J., S.M. de Jong, and A.P.J. de Roo, 2003. A segmentation and classification approach of IKONOS-2 imagery for land-cover mapping to assist flood risk and flood damage assessment, *International Journal of Applied Earth Observation and Geoinformation*, 4:217–229.

Walter, V., 2004. Object-based classification of remote sensing data for change detection, *ISPRS Journal of Photogrammetry and Remote Sensing*, 58:225–238.

Wang, L., W.P. Sousa, P. Gong, and G.S. Biging, 2004. Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of panama, *Remote Sensing of Environment*, 91:432–440.

Welch, R., and M. Ehlers, 1987. Merging multi-resolution SPOT HRV and Landsat TM data, *Photogrammetric Engineering & Remote Sensing*, 53(2):301–303.

Xu, B., P. Gong, E. Seto, and R. Spear, 2003. Comparison of gray-level reduction and different texture spectrum encoding methods for land-use classification using a panchromatic IKONOS image, *Photogrammetric Engineering & Remote Sensing*, 69(5):529–536.

Yu, Q., P. Gong, N. Clinton, G. Biging, M. Kelly, and D. Schirokauer, 2006. Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery, *Photogrammetric Engineering & Remote Sensing*, 72(7):799–811.

Zhang, Q., J. Wang, P. Gong, and P. Shi, 2003. Study of urban spatial patterns from SPOT panchromatic imagery using textural analysis, *International Journal of Remote Sensing*, 24:4137–4160.

Zhou, W., A. Troy, and J.M. Grove, 2008. Object-based land-cover classification and change analysis in the Baltimore metropolitan area using multi-temporal high resolution remote sensing data, *Sensors*, 8:1613–1636.

Zhou, W., G. Huang, A. Troy, and M.L. Cadenasso, 2009. Object-based land-cover classification of shaded areas in high spatial resolution imagery of urban areas: A comparison study, *Remote Sensing of Environment*, 113:1769–1777.

(Received 19 August 2009; accepted 02 November 2009; final version 26 January 2010)

ACT Publications 2009

No. 09-01
Batistella, M., D.S. Alves, E.F. Moran, C. Souza Jr., R. Walker, and S.J. Walsh. People and Environment in Amazonia: The LBA Experience and Other Perspectives. *In* Amazonia and Global Change. M. Keller, M. Bustamante, J. Gash, and P.S. Dias, eds. Geophysical Monograph Series 186. Pp. 1-9.

No. 09-02
Brondizio, E.S., A. Cak, M.M. Caldas, C. Mena, R. Bilsborrow, C.T. Futemma, T. Ludewigs, E.F. Moran and M. Batistella. Small Farmers and Deforestation in Amazonia. *In* Amazonia and Global Change. M. Keller, M. Bustamante, J. Gash, and P.S. Dias, eds. Geophysical Monograph Series 186. Pp.117-124.

No. 09-03
Weng, Q. and D. Lu. Landscape as a Continuum: An Examination of the Urban Landscape Structures and Dynamics of Indianapolis City, 1991-2000, by Using Satellite Images. International Journal of Remote Sensing 30(10): 2547-2577.

No.09-04
Mattos, L., A.D. Didonet, A.J. Baggio, A.T. Machado, E.D. Tavares, H.L.C. Coutinho, J.C. Canuto, J.C.C. Gomes, J.A.A. Espindola, J.F. Ribeiro, L.H.O. Wadt, M.F.S. Borba, M.S.A. Kato, M.A. Urchei P.C. Kitamura, R.T.G. Peixoto. Marco Referencial em Agroecologia. Embrapa.

No.09-05
Weng, Q. and D. Lu. Extraction of Urban Impervious Surfaces from an IKONOS Image. International Journal of Remote Sensing 30(5): 1297-1311.

No.09-06
Mattos, L. and A. Cau. Efetividade do Mecanismo de Desenvolvimento Limpo (MDL) no Contexto das Atividades Agroflorestais no Brasil: Uma Análise Crítica.

No.09-07
Mattos, L. and A. Cau. The Clean Development Mechanism and Agroforestry Activities in the Brazilian Amazon.

No.09-08
Guedes, G.R., S. Costa and E.S. Brondizio. Revisiting the Hierarchy of Urban Areas in the Brazilian Amazon: A Multilevel Approach. Population and Environment 30:159-192.

No.09-09
Brondizio, E.S., E. Ostrom and O.R. Young. Connectivity and the Governance of Multilevel Social-Ecological Systems: The Role of Social Capital. Annual Review of Environmental Resources 34: 253-278.

No.09-10
Siren, A.H. and E.S. Brondizio. Detecting Subtle Land Use Change in Tropical Forests. Applied Geography 29: 201-211.

No.09-11
Andersson, K., T.P. Evans and K.R. Richards. National Forest Carbon Inventories: Policy Needs and Assessment Capacity. Climatic Change 93: 69-101.

No.09-12
Muehlenbein, M.P. The Application of Endocrine Measures in Primate Parasite Ecology. *In* Primate Parasite Ecology. Dynamics and Study of Host-Parasite Relationships. M.A. Huffman and C.A. Chapman, eds. Cambridge University Press.

No.09-13
Muehlenbein, M.P. and M. Ancrenaz. Minimizing Pathogen Transmission at Primate Ecotourism Destinations: The Need for Input from Travel Medicine. Journal of Travel Medicine 16(4): 229-232.