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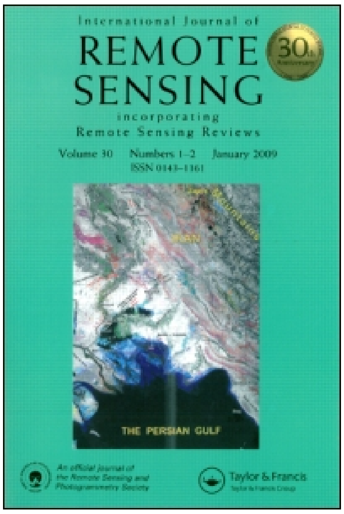

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This research selects two study areas with different urban developments, sizes and spatial patterns to explore suitable methods for mapping impervious surface distribution using Quickbird imagery. The selected methods include per-pixel based supervised classification, segmentation-based classification and a hybrid method. A comparative analysis of the results indicates that per-pixel based supervised classification produces a large number of 'salt-and-pepper' pixels, and segmentation-based methods can significantly reduce this problem. However, neither method can effectively solve the spectral confusion of impervious surfaces with water/wetland and bare soils and the impacts of shadows. To accurately map impervious surface distribution from Quickbird images, manual editing is necessary and may be the only way to extract impervious surfaces from the confused land covers and the shadow problem. This research indicates that the hybrid method consisting of thresholding techniques, unsupervised classification and limited manual editing provides the best performance.

1. Introduction

Impervious surfaces are generally defined as any anthropogenic materials that water cannot infiltrate and are primarily associated with human activities and habitation through construction of transportation and buildings (Slonecker *et al.* 2001). Impervious surfaces have long been recognized as an important variable in many urban or environment-related studies, such as in urban land use classification (Madhavan *et al.* 2001, Phinn *et al.* 2002, Lu and Weng 2006), residential population estimation (Lu *et al.* 2006, Wu and Murray 2007), water quality (Schueler 1994, Arnold and Gibbons 1996, Zug *et al.* 1999, Brabec *et al.* 2002), and urban heat island effect (Weng *et al.* 2004). Research on impervious surface extraction from remotely sensed data has attracted interest since the 1970s and many techniques have been developed for impervious surface mapping (Wu and Murray 2003, Wu 2004, Lu and Weng 2006, 2009, Weng 2007, Powell *et al.* 2008). Much previous research is based on medium spatial resolution images such as Landsat Thematic Mapper (TM), but the mixed pixel problem caused by limited spatial resolution and heterogeneous urban landscapes often results in poor performance (Wu and Murray 2003, Lu and Weng 2006, Weng 2007). Medium spatial resolution imagery thus cannot meet the needs of many practical applications such as urban planning at a local scale. Hence, research on extracting impervious surfaces has shifted to the use of very high spatial resolution

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satellite images such as Quickbird and IKONOS (Cablk and Minor 2003, Goetz *et al*. 2003, Lu and Weng 2009).

In high spatial resolution images such as Quickbird, the mixed pixel problem is significantly reduced, but other problems inherent in the high spatial resolution images present a challenge for automatically mapping impervious surface distribution (Lu and Weng 2009). The problems include: (1) spectral confusion between impervious surfaces and other land covers due to limited spectral resolution (usually only visible and near-infrared (NIR) wavelengths) and high spectral variation within the same land cover due to the very high spatial resolution; and (2) shadows caused by tall objects and the confusion with dark impervious surfaces and water/wetlands (Dare 2005, Li *et al*. 2005, Chen *et al*. 2007, Zhou *et al*. 2009). Figure 1 shows a Quickbird false-colour composite consisting of NIR, Red and Green bands, illustrating the complexity of urban landscapes and showing the potential confusion between impervious surfaces and other land covers. For example, different building roofs, roads, parking lots and shadows appearing as different colours on the images make automatic extraction of impervious surfaces difficult based on spectral signatures.

To reduce the impact of high spectral variation within the same land cover, two methods, texture (Shaban and Dikshit 2001, Zhang *et al*. 2003, Puissant *et al*. 2005, Aguera *et al*. 2008, Pacifici *et al*. 2009) and object-oriented classification (Walter 2004, Mallinis *et al*. 2008, Zhou *et al*. 2008), are often used. Texture refers to the pattern of intensity variations in an image. Many texture measures have been developed (Haralick *et al*. 1973, He and Wang 1990, Unser 1995) and may be used for detection of impervious surfaces. The texture measures can be used for edge detection or for the reduction of spectral variation on the image, depending on the algorithm used. One challenge in the selection of a suitable textural image is to determine the combination

Figure 1. False colour composite of Quickbird bands 4, 3 and 2 (R, G, B) showing the complexity of impervious surfaces (different colours in roads and building roofs, and impacts of shadows from buildings and tree crowns) in the two study areas. (*a*) Santarem, Para, Brazil and (*b*) Lucas do Rio Verde, Mato Grosso, Brazil.

of the following parameters: the choice of the spectral image, the use of a suitable texture measure, the size of the moving window, the quantization level of the image and the inter-pixel distance (Shaban and Dikshit 2001, Pacifici *et al*. 2009). In addition, a good textural image is influenced by the complexity of the land cover types in the study area. The difficulty in identifying a suitable textural image, the uniqueness of the individual study areas, and the high computation cost for calculating textures limit extensive use of textures in image classification, especially in a large area. An alternative is to use object-oriented classification methods, which have been regarded as an effective method for land cover classification in reducing the spectral variation inherent in the same land cover, and have been used for high spatial resolution image classification (Thomas *et al*. 2003, Laliberte *et al*. 2004, Wang *et al*. 2004, Mallinis *et al*. 2008). This method is used in the current research for extracting impervious surfaces from Quickbird images.

Shadow is another important factor reducing the spectral values of the shaded objects or even causing total loss of spectral information, thus influencing the land cover classification with digital image processing. In high spatial resolution images such as Quickbird, the shadow problem is especially serious, as shown in figure 1. Therefore, 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). Shadow detection is used to identify the shadowed pixels through established rules or algorithms, and shadow removal is used to restore the spectral values of the shaded pixel (Lu 2007, Zhou *et al*. 2009). In medium and coarse spatial resolution images, the shadows caused by buildings or vegetation are often mixed with the objects' spectral signatures because of the constraints of spatial resolution; thus, previous research mainly focused on the detection and removal of clouds and cloud-cast shadows (Simpson and Stitt 1998, Wang *et al*. 1999). In high spatial resolution images, problematic shadows are mainly the result of high-rise objects such as buildings and tree crowns (see figure 1). The shadow problem is more obvious in high spatial resolution images, affecting the extraction of biophysical parameters. Therefore, research into the detection and removal of shadows in high spatial resolution images has received increased attention (Dare 2005, Li *et al*. 2005, Lu 2007, Zhou *et al*. 2009). Zhou *et al*. (2009) summarized the methods for the detection and removal of shadows used in previous literature.

The current research aimed to identify suitable approaches to mapping impervious surfaces from very high spatial resolution images. Three different methods, (1) a hybrid method consisting of thresholding, unsupervised classification and manual digitizing, (2) a per-pixel based supervised classification and (3) a segmentation-based supervised classification, were explored in two distinctly different spatial patterns of urban landscapes in Brazil.

2. Study areas

Two urban and urban–rural sites in Brazil (i.e. Santarém in Pará state and Lucas do Rio Verde in Mato Grosso state; see figure 2) were selected in this research for examining the potential techniques to effectively map impervious surface distribution. These sites have significantly different urban landscapes and spatial patterns. Santarém was an important pre-historic occupation area, with one of the largest chiefdoms (i.e. the Tapajós chiefdom) on record in the Amazon at the time of European contact, and with evidence of Paleolithic occupation and early agriculture

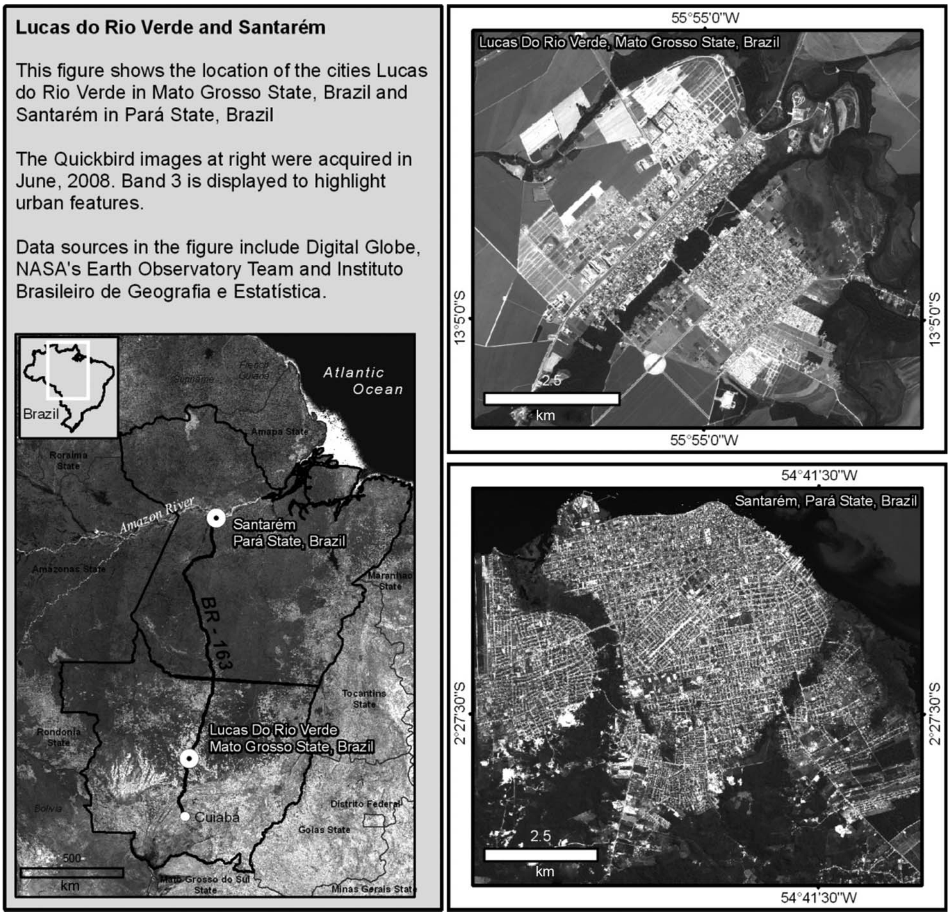

Figure 2. The two study areas, Lucas do Rio Verde in Mato Grosso and Santarém in Pará state, Brazil, illustrating the different spatial patterns of urban landscapes.

dating as far back as 8000 before present (BP) (Roosevelt 1991). Because of its location, at the confluence of the Amazon River and the Tapajós River, Santarém has played an important role in regional transportation. Today, it is also reached by the east–west Transamazon (BR-230) highway and its north–south link, the Cuiabá-Santarém (BR-163) highway, both completed in the early 1970s. The BR-163 links Santarém to Brazil's more industrialized regions to the south. Santarém is thus in the process of being more closely linked with the centre-west of Brazil, and is already linked with global markets acting as a major grain export terminal beginning in 2003.

Lucas do Rio Verde in Mato Grosso, Brazil (hereafter referred to as Lucas) was selected as the study area because of its relatively small size (population of about 30 000) and very complex urban landscapes. The município of Lucas was formed in 1985, through the subdivision of the município of Sorriso. The region is connected to Santarém, a riverine city on the Amazon River. It is at the heart of the soybean growing area of Mato Grosso, and is connected to Cuiabá by the completion of the section of the BR-163 highway running through the município and its county seat. The region is flat and the precipitation pattern permits two annual harvests without irrigation (three with irrigation). The economic base of Lucas is large-scale mechanized agriculture, including the production of soy, cotton, rice, and corn as well as poultry and swine, to take advantage of the grain feed to add value to production. Major poultry and meat producing industries have been introduced and set up industrial complexes to add value to the agricultural output, which is now substantial. The county seat of Lucas is expected to triple in population over the coming decade, maintaining the growth rate that it has had for the past decade.

3. Methods

Quickbird images, which were acquired on 25 June 2008 in Santarém and on 20 June 2008 in Lucas, were selected for exploring the techniques to automatically map impervious surface distribution. Quickbird imagery has four multispectral bands (blue, green, red and NIR) with 2.4 m spatial resolution and one panchromatic band (visible wavelength) with 0.6 m spatial resolution. To make full use of both the multispectral and high spatial resolution features of 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). 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 images were then used for extracting impervious surfaces for both study areas.

3.1 *The hybrid approach for mapping impervious surfaces*

The hybrid method is based on the combined use of a thresholding technique, unsupervised classification and manual editing (see figure 3). Because vegetation has significantly different spectral features with impervious surfaces in the normalized

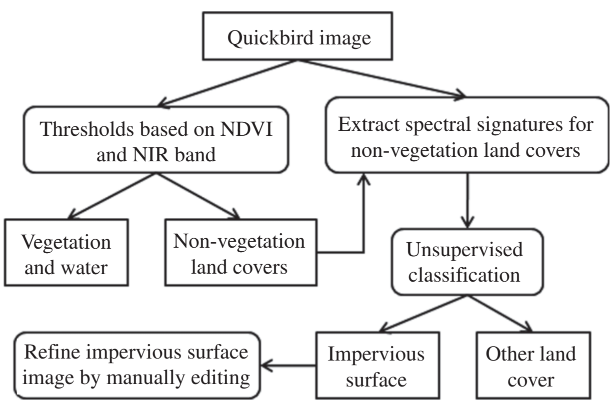

Figure 3. Framework of impervious surface mapping with the hybrid method, which consists of using thresholding techniques on NDVI and NIR to remove vegetation and water, using unsupervised classification to separate the impervious surfaces from other land covers, and using manual editing to refine the extracted impervious surface image.

difference vegetation index (NDVI) image, and clear and deep water bodies have low spectral values in the NIR, the major vegetation and water pixels can be masked out with selected thresholds on NDVI and NIR images. The major steps for the hybrid approach include: (1) producing the NDVI image from Quickbird Red and NIR images and then masking out vegetation with the selected threshold on the NDVI image, and masking water out with the threshold on the NIR image; (2) extracting spectral signatures of the non-vegetation pixels, and using an unsupervised classification algorithm to classify the extracted spectral signatures into 50 clusters. The analyst is responsible for merging the clusters into impervious surface and other classes; (3) manually editing the extracted impervious surface image to eliminate non-impervious surfaces such as bare soils, shadows and wetlands, which have been included with the impervious surface class due to spectral confusion. Because of the huge data volume inherent in very high spatial resolution imagery, the NDVI image was rescaled to an 8-bit integer format to reduce the data volume. Examination of the NDVI image reveals that vegetation types have values > 145 in Lucas and > 155 in Santarém in their NDVI images; thus these thresholds were used to mask out the vegetation. Water with spectral values < 58 in the NIR was also masked out. Although unsupervised classification can separate most impervious surfaces from bare soils and wetlands, there remains much confusion between bare soil and bright impervious surfaces, and among dark impervious surfaces, shadowed impervious surfaces, wetlands or shadows from tree crowns. Therefore, visually examining the extracted impervious surface image is necessary to further refine the impervious surface image quality by eliminating the confused pixels (e.g. bare soils, shadowed land covers without impervious surfaces and wetlands).

3.2 *Use of maximum likelihood classification (MLC) for mapping impervious surfaces*

The hybrid method requires considerable input from the analyst in determining suitable thresholds, identifying land covers and then merging clusters, and manually editing the image. To reduce the human intervention, one alternative is to automatically classify land cover classes with a traditional supervised classification. MLC is the most common supervised classification method that is extensively used for land cover classification. One crucial step is to determine a suitable classification system and to select a sufficient number of representative training samples for each class (Jensen 2004). In this research, the focus was to map impervious surfaces from Quickbird multispectral images. However, impervious surfaces are very complex, as shown in figure 1. No single class can represent all impervious surface materials. In addition, different kinds of impervious surfaces have different spectral signatures, which are often confused with other land covers, such as bare soils, residues in cropped fields, wetlands, water and shadows from buildings or tree crowns. Thus, it is important to identify typical training samples for different land covers. In this research, high-, medium- and low-reflectance impervious surfaces, dirty roads, parking lots and shadowed impervious surfaces were selected. Other land covers include upland forest, riverine forest, agroforestry, grass/pasture, bare soils, shadows in forested areas, cropped fields, water and non-vegetated wetlands. At least 15 training samples for each class were selected. Transformed divergence was used to examine the separability of the selected training samples. MLC was then used to classify the Quickbird multispectral image into a thematic map. The classified image was finally recoded as the impervious surface and others by merging bright-, medium- and low-reflectance impervious surfaces, dirty roads, parking lots, and shadowed impervious surface into a single impervious surface class.

3.3 *Segmentation-based method for mapping impervious surfaces*

Because the per-pixel 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 mitigate this problem (Jensen 2004, Stow *et al*. 2007, Mallinis *et al*. 2008, Zhou *et al*. 2008). Usually, object-oriented methods involve two major steps: one is to produce a segmentation image, and the other is to classify the segments into meaningful classes (Jensen 2004). Object-oriented classification methods have been extensively used for high spatial resolution image classification (Blaschke *et al*. 2004, Stow *et al*. 2007, Mallinis *et al*. 2008). One crucial step in this method is to develop a segmentation image, which is often based on pixel, edge, and region methods (Blaschke *et al*. 2004). In this research, the edge-based segmentation method was used to produce segmentation images based on the Quickbird multispectral images. Figure 4 shows the framework for mapping impervious surfaces based on the segmentation method. The major steps include: (1) producing the segmentation image from the Quickbird multispectral image; (2) converting the segmentation image into a vector format image and removing the segments with small areas; (3) extracting the mean spectral value of each segment for each band; (4) conducting supervised classification for the mean spectral value image; (5) recoding the classified image into impervious surface and other land covers and (6) conducting an accuracy assessment.

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 both study areas. Because of the large-volume data sets in the Quickbird images and the time required for image processing, band 1 is not used during the extraction of the segmentation image. In producing the segmentation image, it is important to identify suitable thresholds to detect edge boundaries and to determine whether or not the pixels belong to the same segment. Therefore, different thresholds ranging from 20, 30, 40, 50 to 60 for edge detection and different segment parameters ranging from 15, 25, 30 to 40 were examined for the 16-bit integer format Quickbird images. Based on the examination of the segmentation images, an edge detection threshold of 50 and a

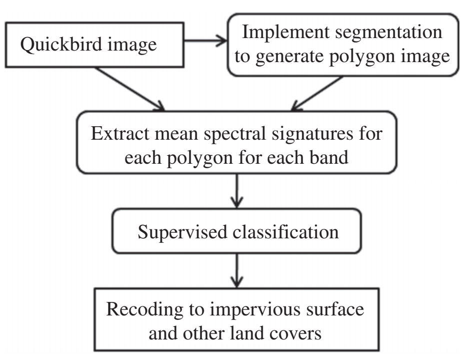

Figure 4. Framework of segmentation-based method for impervious surface mapping.

segment parameter of 30 were finally used in this research. After extracting a mean spectral value for each segment in each band, the training samples were also used to classify the segmentation-based mean spectral value images into a thematic map using MLC. Finally, the classified image was recoded as impervious surface and others.

3.4 *Accuracy assessment*

Accuracy assessment is required for evaluating land cover classification quality or for identifying a suitable classification method by comparing different classification results in a study area. The error matrix approach is often used for accuracy assessment (Foody 2002). Other important accuracy assessment elements, such as overall accuracy (OA), producer's (PA) and user's accuracies (UA), and the 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, Foody 2002, Congalton and Green 2008). In this research, a total of 400 test samples were selected with the random sampling method in Santarém and 450 test samples for Lucas due to its relatively small proportion of urban areas. The analyst then examined each test sample plot to decide whether or not it was correctly classified as impervious surface. PA, UA, OA and KC were then calculated. Because the hybrid method is based on the manually corrected impervious surface images, these extracted impervious surface images have very high accuracy and can be used as reference data for evaluating other results. Therefore, pixel-by-pixel comparison of entire images was also conducted between the result from the hybrid method and the results from the other two methods.

4. Results

A comparative analysis of the accuracy assessment results (see table 1) indicates that the hybrid method provides better accuracy than the maximum likelihood and segmentation-based methods. Considering the kappa coefficients, the hybrid method has kappa coefficient values that are 0.05–0.07 higher in Santarém and 0.15 higher in Lucas than the other two methods. The PA and UA for impervious surfaces based on the hybrid method also have higher accuracy than those from the MLC and

Table 1. Comparison of accuracy assessment results among different classification methods.

		Santarém*				Lucas do Rio Verde†			
Method	Type	PA	UA	OA	KC	PA	UA	OA	KC
MLC	Imps	97.85	88.35	96.50	0.91	75.00	81.82	95.56	0.76
	Other	96.09	99.33			98.01	97.04		
Segmentation-based method	Imps	96.77	86.54	95.75	0.89	83.33	74.07	95.11	0.76
	Other	95.44	98.99			96.52	97.98		
Hybrid	Imps	98.15	94.64	98.67	0.96	93.75	90.00	98.22	0.91
	Other	98.78	99.59			98.76	99.25		

Imps, impervious surface; OA, overall accuracy; PA, producer's accuracy; UA, user's accuracy; KC, kappa coefficient; MLC, maximum likelihood classification.
*400 test sample plots were randomly selected in Santarém and †450 samples were used in the Lucas do Rio Verde study area because of its relatively small proportion of urban area.

segmentation methods. Table 1 shows that when using MLC based on either per-pixel values or segments, the overall performances for extracting the impervious surface are similar, but the human-induced hybrid method improves the performance, especially when the study area is small and the urban landscapes are relatively complex. The older developed urban landscape also provides higher accuracy in Santarém than the relatively newly developed urban landscape in Lucas.

Of note, the per-pixel based MLC and the segmentation-based method have similar accuracy, although the MLC had slightly better OA. However, comparing with the agreement between the hybrid method and the others (see table 2) shows that the segmentation-based method has a slightly better agreement than the MLC. Close examination of the impervious surface images developed from the MLC and segmentation-based methods (see figure 5) revealed that the MLC had a large number of noisy pixels, especially in cropped fields and wetlands, where a large number of pixels were misclassified as impervious surface, while the segmentation-based method significantly reduced this problem. This indicates that the segmentation-based method can reduce the impact of high spectral variation within the same land cover, unlike the per-pixel based methods.

A comparison of the spatial distribution of extracted impervious surface images in both study areas (see figure 5) indicates that the hybrid method can effectively refine the extracted impervious surface by manual editing. The 'salt-and-pepper' effect in the per-pixel based supervised classification is obvious, but this problem can be significantly reduced with both the segmentation-based method and the hybrid method, indicating that reducing the spectral variation within the same land cover is valuable for improving the impervious surface mapping performance. In addition, comparison of the impervious surface images resulting from the selected methods in this research indicates that a combination of manually editing and the segmentation-based method may significantly reduce the time and labour involved in refining the impervious surface image.

5. Discussion

For high spatial resolution imagery, the major factors affecting impervious surface mapping include high spectral variation within the same land cover, spectral confusion among different land covers, and problematic shadows. Examination of the test samples indicates that the major misclassification errors are a result of confusion among the particular land covers: dark impervious surfaces are often confused with water features, wetlands and shadows, while bright impervious surfaces are often

Table 2. Comparison of accuracy agreement between the selected methods.

		Santarém			Lucas do Rio Verde		
Comparison of methods	Land cover	PA	UA	OA	PA	UA	OA
Hybrid vs. MLC	Imps	82.38	92.78	94.31	76.57	69.84	93.52
	Others	98.01	94.71		95.72	96.93	
Hybrid vs. Segmentation-based method	Imps	82.64	92.84	94.39	77.65	70.32	93.73
	Others	98.03	94.8		95.79	97.09	

Imps, impervious surface; OA, overall accuracy; PA, producer's accuracy; UA, user's accuracy; MLC, maximum likelihood classification.

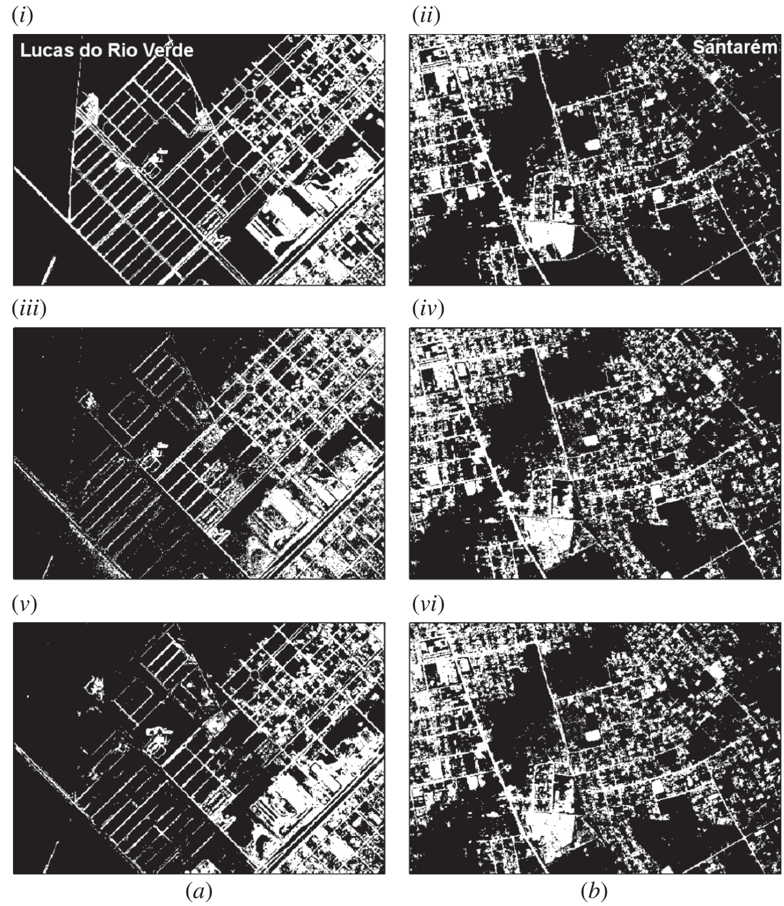

Figure 5. A comparison of impervious surface images developed from different classification methods for both study areas (*a*) Lucas do Rio Verde in Mato Grosso and (*b*) Santarém in Pará state, Brazil: (*i*) and (*ii*) the hybrid method; (*iii*) and (*iv*) maximum likelihood classification; (*v*) and (*vi*) the segmentation-based method.

confused with particular types of building roof tops, bare soils and crop residuals. Figure 6 provides examples showing the similar spectral signatures of land cover classes in the Lucas study area, indicating that they are not adequately separated based on pure spectral signatures.

The high spectral variation inherent in Quickbird imagery results in a ‘salt-and-pepper’ effect in the classification image when per-pixel based methods are used, as shown in figure 5. This problem is especially obvious in mapping impervious surface distribution because different kinds of construction materials have different spectral reflectance values (Lu and Weng 2009). Thus, reducing the spectra variation in the impervious surfaces can improve classification performance. The per-pixel based MLC method cannot reduce the spectral variation, thus the classification image has a large number of ‘salt-and-pepper’ pixels, while the segmentation-based method can reduce the spectral variation through the extracted segments. Previous research has also indicated that the segmentation-based classification method is helpful, especially

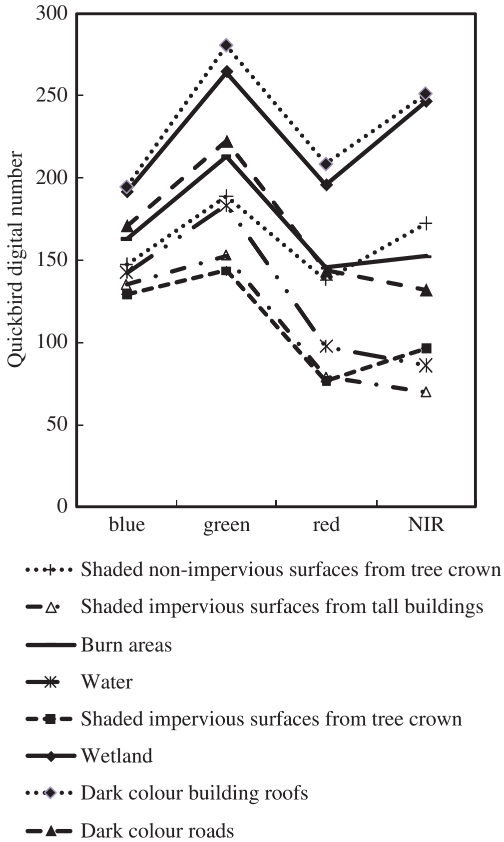

Figure 6. A comparison of spectral signatures among low reflectance objects, illustrating the potential difficulty in the separation of these land covers based on spectral signatures.

in high spatial resolution images, for improving classification performance (Thomas *et al.* 2003, Laliberte *et al.* 2004, Wang *et al.* 2004, Mallinis *et al.* 2008).

The spectral confusion among different land covers in high spatial resolution imagery is an important factor contributing to the difficulty in the production of high-quality classifications (Lu and Weng 2009). The major reason for this confusion is that the spectral bands in high spatial resolution imagery have only visible bands and one NIR band, and lack shortwave infrared bands. For specific remotely sensed data, it is difficult to keep all the spatial, spectral, and radiometric resolutions at high levels due to the trade-off among these resolutions. Thus, for high spatial resolution images such as Quickbird and IKONOS, spatial resolution is very high, but spectral bands have to keep a limited number. In urban landscapes, high spatial resolution is important, especially for impervious surface mapping because of the complexity of urban land cover. However, as shown in figure 6, impervious surfaces can be confused in spectral signatures with different land covers. In this way, selecting a suitable image acquisition date is important. In this research, the Quickbird images for both study areas were acquired in late June 2008 when the crops had already been harvested. Crop residues or bare soils in the cropped fields appeared to have similar spectral signatures to some impervious surfaces, resulting in misclassification. We tested another Quickbird image with the acquisition date of 2 April 2007, when crops were still in the growing stage in Lucas. In this image, the spectral signatures of the growing crops were significantly different from the impervious surfaces, and thus they can be easily classified and separated. In both study areas, dirt roads and some building roof tops were often confused with bare soils or some harvested fields. In Santarém, we even found that burned areas were confused with dark impervious surface because of their low spectral signature values. This research has shown that the impervious surfaces cannot be completely distinguished from other land covers based on spectral signatures alone. Incorporation of other data such as lidar or use of advanced methods may improve the impervious surface mapping performance (Thomas *et al.* 2003, Guindon *et al.* 2004, Pacifici *et al.* 2009).

The shadows cast from tall objects are another important factor affecting the classification accuracy (Zhou *et al.* 2009). Shadows reduce the spectral values of true land cover under the shadows, and this impact is different, depending on the degree of shadowing. Although previous research has explored the methods for detection and removal of shadows in high spatial resolution images (Dare 2005, Li *et al.* 2005, Lu 2007, Zhou *et al.* 2009), these methods cannot completely extract shaded impervious surfaces from other land covers such as water because of their similar spectral signatures. A simple method is to visually interpret the image and manually edit the shaded impervious surfaces, because human beings can comprehensively use colour, shape, spatial patterns and contextual information, along with knowledge and experience, to interpret different impervious surfaces and shaded areas in the high spatial resolution images. The hybrid method developed in this paper has shown the importance of human-involved editing in improving the impervious surface mapping performance.

6. Conclusions

This research examined per-pixel based, segmentation-based and hybrid methods for the mapping of impervious surfaces using high spatial resolution data in two different urban landscapes in Brazil. We found that the hybrid method provided the best performance, but it required considerable time and labour involving manual editing and refinement of the impervious surface image. The segmentation-based method provided similar accuracy to the MLC method because of the difficulty in automatically distinguishing impervious surface from bare soils, shadows and wetlands due to the spectral confusion between them. However, the segmentation-based method reduced the impact of spectral variations within the same land cover, thus reducing the ‘salt-and-pepper’ effects on the final results.

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