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Abstract. Accurately detecting urban expansion with remote sensing techniques is a challenge due to the complexity of urban landscapes. This paper explored methods for detecting urban expansion with multitemporal QuickBird images in Lucas do Rio Verde, Mato Grosso, Brazil. Different techniques, including image differencing, principal component analysis (PCA), and comparison of classified impervious surface images with the matched filtering method, were used to examine urbanization detection. An impervious surface image classified with the hybrid method was used to modify the urbanization detection results. As a comparison, the original multispectral image and segmentation-based mean-spectral images were used during the detection of urbanization. This research indicates that the comparison of classified impervious surface images with matched filtering method provides the best change detection performance, followed by the image differencing method based on segmentation-based mean spectral images. The PCA is not a good method for urban change detection in this study. Shadows and high spectral variation within the impervious surfaces represent major challenges to the detection of urban expansion when high spatial resolution images are used.

Keywords: urban expansion, QuickBird, matched filtering, image differencing, principal component analysis, segmentation.

1 INTRODUCTION

Urban land use spatial distribution and dynamic change patterns are important data sources for applications and research related to urban planning and management, environmental and socioeconomic conditions. However, timely and accurate development of urban land use spatial data from remotely sensed data is often difficult due to the fact that urban landscapes are a complex combination of different impervious surfaces (e.g., buildings, parking lots and roads), grass, trees, soil, and water. In coarse and medium spatial resolution images such as those produced by the Landsat Thematic Mapper (TM) sensor, mixed pixels have been recognized as a problem affecting the effective use of remotely sensed data in land cover classification and change detection [1]. Detection of urban change using multitemporal remotely sensed data is a challenge due to the unique characteristics of urban landscapes: urban change usually accounts for a small proportion of the study area and is scattered in different locations; and urban change is often confounded with other land cover changes. Although the mixed pixel problem can be reduced in high spatial resolution images such as QuickBird, there are other challenges for automatically mapping land cover distribution. Figure 1 (QuickBird images acquired in 2008 and 2004 displayed as false color composites by assigning bands 4, 3, and 2 as red, green and blue) indicates the complexity of impervious surfaces, which appear as different colors, depending on their different construction materials. For a single date QuickBird image, the challenges include (1) high spectral variation within the same land cover class, especially impervious surface features; (2) shadows cast by tall objects such as buildings and trees, reducing the spectral values of the shaded land covers; (3) limited spectral bands, especially the lack of shortwave infrared bands, resulting in spectral

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confusion between the different land cover classes; and (4) large data redundancy and large volume data sets due to high spatial and radiometric resolutions. For example, because of very high spatial resolution in the QuickBird panchromatic band (i.e., 0.6 m), the same building roof or highways are recorded as the same or similar digital numbers, resulting in data redundancy and requiring more time and space for computer processing. In contrast, the buildings may have significantly different spectral signatures due to the impacts of sun elevation angle and shadows, as well as different construction materials, resulting in poor classification accuracy based on automatic computer processing. For multitemporal QuickBird images, impervious surfaces in the same physical location on different image acquisition dates could have different spectral signatures due to the different levels of moisture or due to changes in construction materials, as shown in Figure 1. Also geometric errors between the multitemporal images and different sizes of shadows caused by different sun elevation angles and tall objects are important factors resulting in change detection errors.

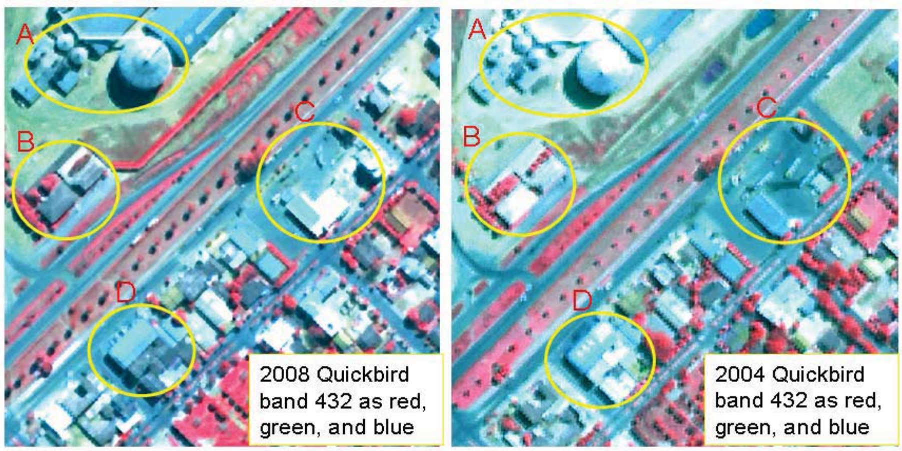

Fig. 1. These QuickBird false color composites using bands 4, 3, and 2 as red, green, and blue, illustrating the complexity of different impervious surfaces (A, B, C and D on both images show the different colors in the same locations)

Change detection techniques can be roughly grouped into two categories: (1) those detecting binary change/non-change information, such as using image differencing, image ratioing, vegetation index differencing, and principal component analysis (PCA); and (2) those detecting a detailed 'from-to' change trajectory, such as using the post-classification comparison and hybrid change detection methods [2]. Previous literature has reviewed many change detection techniques [2-6]. Due to the importance of monitoring change of Earth's surface features, research on change detection techniques has been an active topic in the past three decades and a large number of techniques have been developed, as summarized in the literature review papers [2-6]. As high spatial resolution images, such as QuickBird, become readily available, use of these high spatial resolution images for extracting urban biophysical parameters has become more and more popular, especially in a relatively small area such as an individual city or town [7-10]. However, detection of urban expansion with multiple dates of very high spatial resolution images such as QuickBird or IKONOS is still a challenge. The possible reasons for this include (1) lack of suitable techniques to solve the problems caused by such factors as geometric errors and shadows; (2) the high cost of images; (3) the requirement of high-end facilities for image processing due to the large volume of the data sets; and (4) QuickBird and IKONOS are "on demand" products: unlike sensors such as TM and MODIS, they are not always recording images so there is a much more limited archive of imagery available which limits temporal analysis. In practice, monitoring processes of urbanization is an urgent task. Although medium spatial resolution images such as Landsat have been extensively used for urban land use/cover classification, its mixed pixel problem prohibits generating precise urban land use/cover data sets and loses the details of spatial patterns of urban land use structure. High spatial resolution images such as SPOT HRG and QuickBird have recently become important data sources for examining urban land use patterns and dynamic changes. However, it is not clear which method is suitable for detecting urbanization, especially in a complex urban-rural frontier. Based on the specific features in very high spatial resolution images (e.g., rich spatial information, high spectral variation within the same land cover, spectral confusion between impervious surfaces and other land covers, shadow problem), the designed method for urban land use/cover classification or change detection should have the capability to reduce these problems. Traditional per-pixel spectral-based methods cannot effectively handle these issues, thus the objective of this research is to identify suitable approaches to detect urban expansion based on multitemporal QuickBird images in a relatively new urban landscape through a comparative analysis of selected methods.

2 STUDY AREA

Lucas do Rio Verde in Mato Grosso State, Brazil, (hereafter referred to simply as Lucas) is selected as the study area because of its relatively small size (ca. 35,000 population, http://www.lucasdorioverde.mt.gov.br/), very complex urban landscape, and its rapid urbanization rate that is very suitable for the exploration of urban expansion detection with high spatial resolution images. The município (county) of Lucas was formed in 1988. The region is at the heart of the soybean growing area of Mato Grosso and is connected to Santarém, a port city on the Amazon River, and to Cuiabá by the BR-163 highway which runs through the município and its county seat (see Figure 2). 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 set up industrial complexes to add value to the agricultural output which is now substantial (http://www.lucasdorioverde.mt.gov.br/). The county seat of Lucas is expected to triple in population over the coming decade, maintaining a growth rate that it has had for the past decade (personal communication with secretariat for planning at Lucas).

3 METHODS

3.1 Image preprocessing

Two QuickBird images, which were acquired on 17 June 2004 with sun elevation angle of 45.8 degree and sun azimuth angle of 34.7 degree, and on 20 June 2008 with sun elevation angle of 48.7 degree and sun azimuth angle of 28.4 degree, were used in this research. The QuickBird image has four multispectral bands (i.e., blue, green, red, and near infrared wavelengths) with 2.4 m spatial resolution and one panchromatic band 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 [11-17]. The wavelet merging technique is regarded as a good method for preserving the multispectral features while improving spatial features in the output result [18-19], thus it 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 new fused multispectral images were used for urban expansion detection.

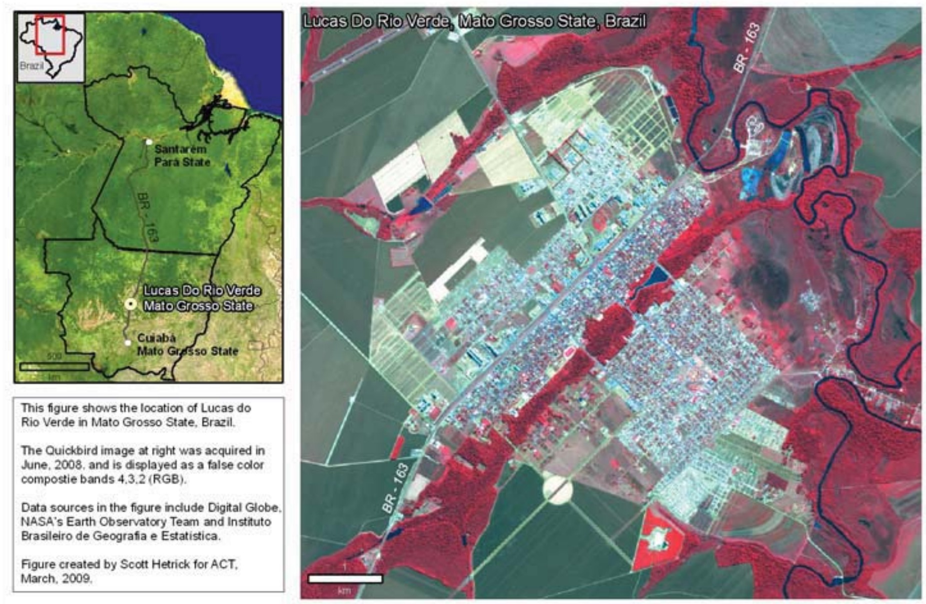

Fig. 2. Study area – Lucas do Rio Verde, Mato Grosso, Brazil.

Both QuickBird multispectral images were geometrically registered into the UTM coordinate system. Accurate geometric co-registration of multitemporal imagery is required before they can be used for change detection. In this research, 25 control points were selected from road intersections, which were evenly distributed within the image. The geometric error was 0.594 pixels for the image-to-image registration between the 2008 and 2004 images. In addition to producing high quality image-to-image registration, accurate radiometric and atmospheric calibration or image-to-image normalization is also critical [2, 6] to ensure that the spectral differences between multitemporal images represent true change in land cover and the spectral properties of non-change objects have stable values. In this research, image-to-image normalization for both QuickBird multispectral images was conducted with the bright-dark object based normalization technique [20-21], assuming that the same invariant objects in both QuickBird data have similar spectral features. Therefore, the intersection of roads, roofs of large buildings, and water bodies were selected for establishing the regression equations for image-to-image normalization. The 2008 image was used as the reference image and the 2004 image was used as the subject image. A regression equation for each band pair between 2008 and 2004 was established to calibrate the 2004 multispectral image.

3.2 Image derivation from QuickBird images

3.2.1 Impervious surface mapping with a hybrid method

A challenge in using high spatial resolution images for automatically mapping impervious surface distribution is to distinguish impervious surfaces from bare soils, shadows and water/wetlands, because bright impervious surfaces are often confused with bare soils and dark or shaded impervious surfaces are confused with tree-crown cast shadows and water/wetlands [10, 22]. A hybrid method based on stratification, unsupervised classification (i.e., ISODATA), and manual editing for mapping impervious surface distribution was used [22]. In general, impervious surfaces have much higher spectral signatures than vegetation types in red-band data, and clear and deep water bodies have lower spectral signatures than vegetation types in the near-infrared (NIR) image, thus, normalized difference vegetation index (NDVI) and NIR images can be used to mask out the pixels of vegetation and water on the QuickBird image. The spectral signature for the non-vegetation (e.g., different kinds of impervious surfaces such as building roofs, roads/streets and parking lots, bare soils, and non-vegetated wetland) can then be extracted, based on the combination of the QuickBird spectral image and the remaining non-vegetation image. Unsupervised classification was then used to classify the non-vegetation spectral image into 50 clusters. The analyst was responsible for merging the clusters into an impervious surface class or other land covers (i.e., any land covers except impervious surfaces). The impervious surface image was overlaid on the QuickBird color composite to examine the misclassification between dark or shadowed impervious surfaces and water/wetland/other shadowed areas, and manual editing was used to correct this misclassification.

Accuracy assessment for the classified impervious surface image was conducted, based on randomly selected test sample plots. A total of 450 sample plots were randomly selected for each classified image. The analyst was responsible for examining each sample plot to decide whether it was impervious surface or not. The accuracy assessment results indicated an overall classification accuracy of greater than 98% and kappa coefficients greater than 0.95 for both 2008 and 2004 impervious surface images [22]. These high accuracies indicated that the classified impervious surface images can be used as reference data for assessing other impervious surface data which were developed with other methods.

3.2.2 Extraction of mean spectral signatures for segments

Previous research has indicated that object-based classification methods outperformed the traditional per-pixel based methods in land cover classification when very high spatial resolution image are used [9, 23-26]. 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 [23]. One critical step in this method is to develop a segmentation image, which is often based on pixel, edge, and region methods [27]. The major steps for the segmentation-based method used in this research include: (1) producing the segmentation image from the QuickBird multispectral image; (2) converting the segmentation image into vector format; and (3) extracting the mean spectral value for each segment for each band.

The edge-based segmentation method was used to produce segmentation images. Different thresholds, ranging from 20, 30, 40, 50, to 60 for edge detection and different parameters ranging from 15, 25, 30, to 40 for segments, were examined for the 16 bit integer format of QuickBird multispectral images. Based on the examination of segmentation images, an edge detection threshold of 50 and segment parameter of 30 were used in this research. The majority filter with 5x5 window size was used on the segmentation image for removing small segments. The mean spectral signature for each segment was then extracted with a mean algorithm based on the combination of segmentation image and QuickBird multispectral image. The extracted mean spectral images were then used for urbanization detection.

3.2.3 Impervious surface mapping with the matched filtering method

The matched filtering approach is used to find the abundance of a user-defined endmember with the partial unmixing technique, which maximizes the response of the selected endmember and suppresses the response of the background [28-31]. Unlike the complete unmixing method which requires the collection of the spectral features of all endmembers to get an accurate analysis, the matched filtering technique only needs the spectral features of the chosen target, without need of other endmembers, to "match" the image in order to get matched filter score. Therefore, this approach provides a rapid way to detect the specific material based on the matches to the selected endmember spectra. The resultant image appears as a gray-scale image representing the relative degree of match to the selected spectra.

The matched filtering method is often used for extracting specific targets from hyperspectral images [28-31]. In this research, this method was used to map impervious surfaces from QuickBird multispectral images.

Ridd [32] assumed that land-cover in urban environments is a linear combination of three components: vegetation, impervious surfaces, and soil (V-I-S). The V-I-S model provides a guideline for decomposing urban landscapes and a link for these components to remote-sensing spectral characteristics. From the view of remote sensing data, impervious surfaces have high spectral variation, for example, bright building roofs have very high spectral signature which is confused with soils, and dark roads and building roofs have very low spectral signature which is often confused with water/wetland/shadow. We can assume that remote sensing data be a combination of three components: low-albedo objects, high-albedo objects, and vegetation. Low-albedo objects represent the land covers with low spectral signatures in the visible and near-infrared wavelengths, such as dark impervious surfaces, water/wetland, and shadows from tall objects. High-albedo objects represent the land cover with high spectral signatures in visible and near-infrared wavelengths, such as bright impervious surfaces, bare soil, and crop residues in the fields. Vegetation such as forest, agroforestry, and pasture/grass, has high spectral signatures in the NIR wavelength. Impervious surfaces can be extracted from the combination of high-albedo and low-albedo fraction images. Figure 3 illustrates the strategy for mapping impervious surface images with the matched filtering method.

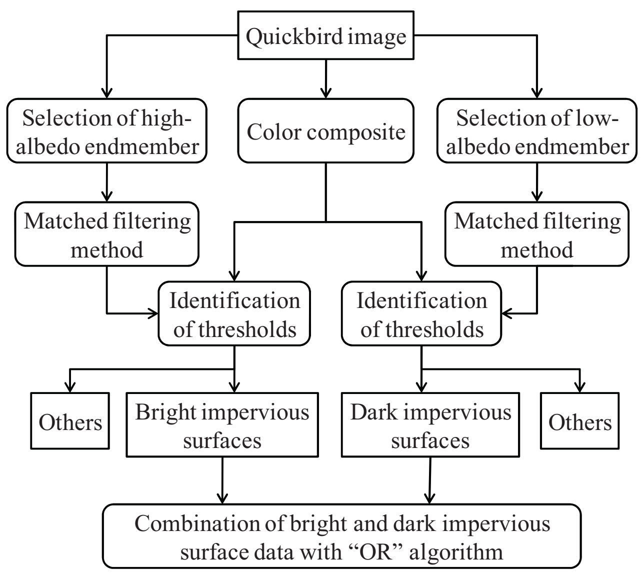

Fig. 3. Strategy of impervious surface mapping with the matched filtering method.

In this research, typical sites from bright building roofs and dark roads were first selected as potential endmembers. High-albedo and low-albedo endmembers were also selected from the scatterplot based on red and NIR bands and their spectral curves were compared with the typical sites. The endmembers whose curves were similar but located at the extreme vertices of the scatterplot were finally selected so that the selected high-albedo and low-albedo endmembers represent impervious surfaces, not bare soils or water. The matched filtering method was used to develop the high-albedo and low-albedo fraction images from QuickBird multitemporal images respectively. The extracted high-albedo and low-albedo fraction images were overlaid on the QuickBird color composite to visually examine the data distribution of impervious surfaces in order to identify suitable thresholds for separating the impervious surfaces from other land covers. Based on the analysis of impervious surfaces from high-albedo and low-albedo fraction images, a threshold of 0.4 for both fraction images was found to be optimal to extract impervious surfaces. Finally a combination of high- and low-albedo images was used to produce a new image called impervious surface image by using the threshold for both albedo images, i.e., if the pixel value was greater than 0.4 in either high-albedo or low-albedo fraction images, the pixel was assigned the value of one, representing impervious surface in the new image; otherwise, the pixel was assigned a zero value.

3.3 Urban expansion detection

Three change detection methods were examined in this research. They include (1) image differencing, (2) PCA, and (3) comparison of classified impervious surface images which were developed with the matched filtering method. For image differencing and PCA methods, two data sets were used, they are original per-pixel spectral images and segmentation-based mean spectral images for both-date QuickBird multispectral images. The classified impervious surface image in 2008 which was developed with the hybrid method was used to modify the change detection results. The subsections described these methods in detail.

3.3.1 Urban expansion detection with the image differencing

Image differencing is often used to detect binary change and non-change information. It involves the subtraction of two spatially registered images pixel by pixel. The pixels of a changed area are expected to be distributed in the two tails of the histogram of the resultant image, and the unchanged area is grouped around zero [2, 23, 33]. This method is simple and makes it easy to interpret the resultant image. Much previous research has indicated the usefulness of the visible red band image in change detection analysis [33-36] because vegetation has low reflectance but impervious surfaces have high reflectance in this band. One critical issue is to define the appropriate thresholds for identifying the change from non-change areas. In general, two methods are often used for selection of thresholds [2-3]: one is based on the interactive procedure or manual trial-and-error procedure – an analyst interactively adjusts the thresholds and evaluates the resultant image until satisfied; and the other is based on statistical measures – selection of a suitable standard deviation from a class mean.

In this research, the image differencing method was conducted separately on the segmentation-based red-band images and original pixel-based red-band images between the two QuickBird data. The manual trial-and-error procedure was used to identify the threshold. The binary change and non-change image was combined to the classified impervious surface image from the hybrid method to produce the urban expansion detection image. In the classified impervious surface image from the 2008 QuickBird image, the impervious surface class and other land cover were assigned as 1 and 0 respectively, and in the binary change and non-change image developed from 2008 and 2004 QuickBird images, changed and non-changed pixels were assigned as 1 and 0 as well. If a pixel value was 1 in both images, this pixel was defined as urban expansion and assigned as 1; otherwise, this pixel was defined as other land covers, and assigned as 0.

3.3.2 Urban expansion detection with the principal component analysis method

PCA is often used to detect change and non-change information [37-39]. Two date image data are superimposed and treated as a single data set. PCA is implemented on the stacked dataset. The major component images often contain the overall radiation difference that represents different land-cover types. The minor component images contain land-cover changes between the different dates [23, 33]. Usually, the higher components are used to analyze the land-cover change. In the PCA-based change detection method, two important issues require attention. One is to identify a suitable component for the change detection analysis, and the other is to select suitable thresholds to distinguish the binary change and non-change areas. It is often difficult to identify the change areas without a careful examination of the components and reference data.

In this research, the QuickBird images between 2008 and 2004 were used for change detection with the PCA method. Two data sets, one from the per-pixel based multispectral images, and the other from the segmentation-based mean spectral images, were used respectively. The eigenvector and corresponding component images were examined to identify the potential component images for detection of binary change and non-change information. The thresholds for separating change from non-change were then identified based on the trial-and-error procedure. The same rule as described in the previous section was used to develop the urban expansion image based on the PCA-based binary change and non-change image and the 2008 classified impervious surface image with the hybrid method.

3.3.3 Urban expansion detection with the comparison of classified impervious surface images with matched filtering method

The matched filtering method was used to produce an impervious surface image for each QuickBird image, then a post-classification comparison method was used to produce the urban expansion images between 2004 and 2008 based on the following rules: if a pixel in a previous date image is not an impervious surface, but it becomes impervious surface in the posterior date, this pixel is defined as urban expansion and assigned 1; otherwise, this pixel is defined as others and assigned 0. Because of the impacts of bare soil and water or wetland on the impervious surface images, it was necessary to remove the bare soil and water or wetland impacts by using the 2008 classified image based on following rules: if a pixel is detected as urban expansion based on the comparison of classified impervious surface image with the matched filtering method, but not impervious surface in the 2008 classified impervious surface image with the hybrid method, re-assign this pixel to other land cover.

3.4 Accuracy assessment for the urbanization detection results

A common method for accuracy assessment is through the use of an error matrix. Previous literature has provided the interpretations and calculation methods to determine overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and Kappa coefficient [40-44]. However, accuracy assessment for change detection results is often difficult and time-consuming because it requires the examination of the sample plots on both dates to identify that the individual plot is changed or not and how it was changed. Since the 2008 and 2004 classified impervious surface images with the hybrid method had very high accuracies [22], they were used to generate a change detection result with the post-classification comparison method, and the change detection result was assumed to be good enough for use as a reference image to evaluate the results from other change detection methods.

4 RESULTS

4.1 Analysis of urban expansion with the image differencing method

Use of segmentation-based mean spectral images in the image differencing method provided better change detection accuracies than the use of per-pixel red-band images between 2004 and 2008, as shown in Table 1. Although overall accuracies for both types of images (i.e., per-pixel red-band image and segmentation-based red band mean spectral image) between 2004 and 2008 seem similar, the producer's and user's accuracies for impervious surfaces indicate that the segmentation-based mean spectral images provide significantly better results than per-pixel-based images. A comparison of original per-pixel red band image and segmentation based red-band image, as shown in Figure 4, indicated that segmentation-based image reduced spectral variation within the same land cover and increased the land cover homogeneity, thus increasing the change detection performance.

Table 1. Comparison of accuracy assessment results between 2004 and 2008.

Method	Images used	Land cover	PA	UA	OA
Image differencing	Per-pixel spectral red-band images	Impervious	64.79	54.35	96.44
		Others	97.75	98.53	
	Segmentation-based red-band mean spectral image	Impervious	74.31	65.58	97.30
		Others	98.30	98.87	
PCA	Per-pixel spectral bands 2, 3, and 4	Impervious	43.52	42.33	94.67
		Others	97.14	97.27	
	Segmentation-based mean-spectral bands 2,3,4	Impervious	40.83	45.01	94.30
		Others	97.25	96.76	
Comparison of classified data	Classified impervious surface images developed from per-pixel spectral bands with matched filtering method	Impervious	93.03	63.77	98.06
		Others	98.23	99.76	

Fig. 4. Comparison of original red-band image (a) and corresponding segmentation-based image (b).

4.2 Analysis of urban expansion with principal component analysis method

The eigenvector of PCA based on 2004 and 2008 QuickBird images (see Table 2) indicated that PC1 was a linear combination of both date images, representing the radiance of stable elements in both dates, although it also highlighted the new roads because of its high spectral values in visible and NIR bands. PC2 was the image difference between NIR and visible bands, thus representing vegetation information. PC3 was the difference between both-date images, indicating the land cover change information. PC4 was the difference of vegetation indices (NIR-visible bands 1 and 2) between both dates, representing the vegetation changes. PC5 was the sum of image difference between red and green band image, thus, not representing the true land cover change. PC6 was the image difference between both date image differencing results of red and green, thus representing the land cover changes. Figure 5 illustrates an example for the comparison of red-band images between 2004 and 2008, and the six PCs based on bands 2, 3, and 4 from both 2004 and 2008 (band 1 was not used because of its high correlation coefficients with bands 2 and 3, and large data volume). Comparison of the red-band images between 2004 and 2008 indicated the rapid urbanization, especially the road construction. Examination of the PCs and their corresponding eigenvector values indicated that PC6 provided the best performance in highlighting impervious surface change information, thus PC6 was used for developing binary change and non-change areas through the thresholding technique, based on manual trial-and-error procedure.

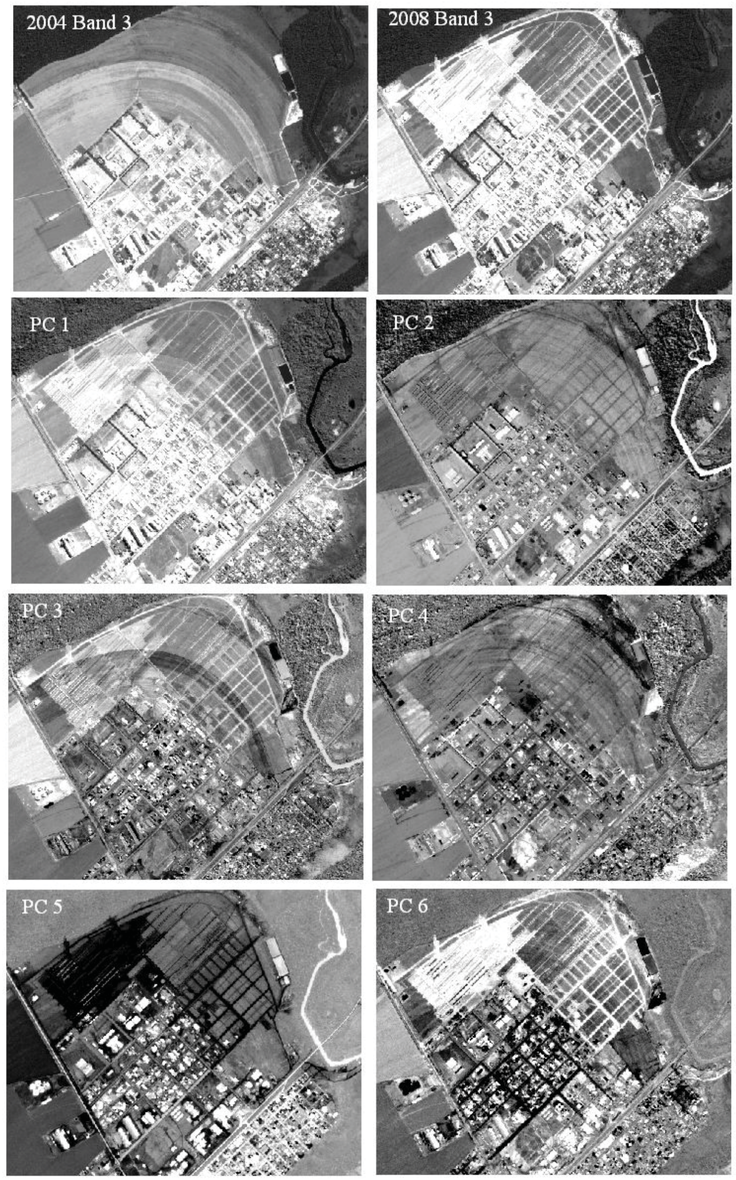

Fig. 5. A comparison original band 3 images from 2004 and 2008 QuickBird images and the principal components of both dates stacked for bands 2, 3, and 4 (band 1 is not used due to its high correlation with band 2 and 3).

The combination of the binary change and non-change images and the 2008 classified impervious surface image with the hybrid method allowed urban expansion information to be developed between 2004 and 2008. The accuracy assessment results are also summarized in Table 1. Although overall accuracies were very high, the producer's and user's accuracies for impervious surfaces were relatively poor based on the PCA change detection method, either based on per-pixel multispectral images or segmentation-based mean-spectral images. This implies the difficulty in detecting impervious surface change with PCA method because some impervious surface changes were appeared in different PCs and no single PC can extract all change information. For example, Figure 5 shows that PC1, PC3, PC5 and PC6 highlighted parts of change information, especially the roads. This indicates that use of one PC cannot effectively extract all changed information. However, use of more PCs for change detection produces the difficulty in the selection of thresholds for separating impervious surfaces from other land cover changes.

Table 2. Eigenvector of principal component analysis based on two-date QuickBird images.

Year	Band	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
2004	Green	0.335	0.288	-0.315	0.273	0.476	0.636
	Red	0.430	0.446	-0.332	0.373	-0.309	-0.521
	NIR	0.241	-0.484	-0.718	-0.434	-0.044	-0.044
2008	Green	0.461	0.032	0.327	-0.342	0.625	-0.415
	Red	0.543	0.125	0.336	-0.378	-0.533	0.385
	NIR	0.372	-0.683	0.236	0.581	-0.038	0.009

4.3 Analysis of urban expansion with the comparison of classified impervious surface images with the matched filtering method

The matched filtering method is very effective for extracting specific materials from multispectral images. As illustrated in Figure 6, bright impervious surfaces (e.g., roads and building roofs with high spectral values) and soils are highlighted in the high-albedo fraction images and dark impervious surfaces (roads and building roofs with low spectral values as appeared as dark color on the image) and water are highlighted in the low-albedo fraction image. Therefore, use of suitable thresholds can effectively extract impervious surfaces from both fraction images respectively. A comparison of accuracy assessment results (see Table 1) indicated that the comparison of classified impervious surface images with the matched-filtering method provides the best result, followed by the image differencing method based on the segmentation based mean spectral images.

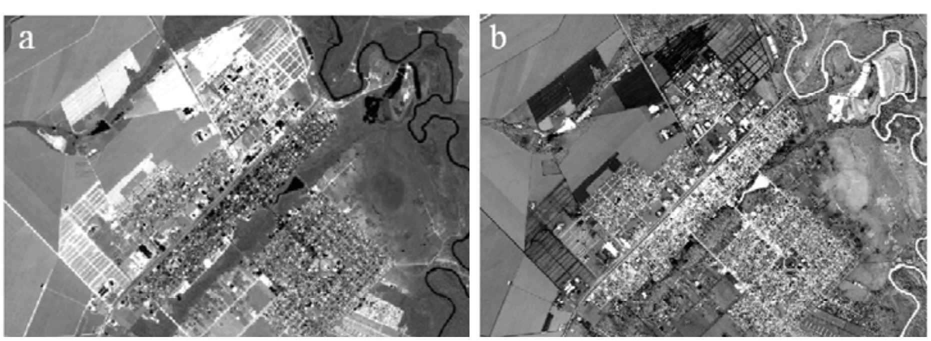

Fig. 6. High-albedo (a) and low-albedo (b) images developed with the matched filtering method from the 2008 QuickBird image.

4.4 Comparison of different change detection methods

The comparison of classified impervious surface images with the match filtering method provides the best change detection performance because impervious surfaces are a stable variable without impacts from the different construction materials and colors, as well as the vegetation phenology and moisture. The PCA or image differencing methods are based on spectral signatures, which the urban land uses have wide spectral variation, depending on the construction materials and colors, as well as moisture. Thus, the change detection methods based on spectral signatures is not suitable for urban change detection.

Comparison of PA and UA in Table 1 indicates that PA often has higher values than UA, except for the PCA-based change detection method. This is because the selection of thresholds is subjective, depending on the analyst's experience, the method to determine the threshold, and the knowledge of the study area. When we identify the threshold, we try to include all imperious surfaces, as used in matched filtering method, or include all changed areas, as used in the image differencing method. In the matched filtering method, a relatively small threshold was selected in order to include all impervious surfaces, but the disadvantage was that some non-impervious surface land covers such as bare soils and wetland whose spectral signatures were similar were misclassified as impervious surfaces. Therefore, PA will be much higher than UA. The similar situation was in the image differencing based method. Some fake changes such as some agricultural lands (e.g., from cropped fields to growing crops between two dates) may be confused with the true land cover change such as from agricultural land to urban lands. This problem is common because the image differencing method is based on spectral signatures, which is affected by the crop phenology. For the PCA-based method, the PA and UA have similar values, because only one PC, whose obvious change of interesting land cover was highlighted, was used for change detection. The major problem in using PCA is that the change detection accuracy is poor in urban landscapes, because changed information was included in different PCs and the difficulty in identifying suitable thresholds to separate urban change from other changes.

5 DISCUSSION

5.1 Impacts of remote sensing data per se

The urban landscape is often very complex, with different impervious surfaces having different spectral signatures (see Figure 1) and their spectral signatures are often confused with non-impervious surface land covers such as bare soils and water or non-vegetated wetlands [22]. Another issue with QuickBird images is the limited number of spectral bands, especially lack of short-wavelength infrared bands, which are most helpful for land cover classification [33]. The spectral signatures for man-made features in multispectral images could change over time because of reconstruction of roads or building roofs with different materials, as shown in Figure 1, thus detection of urban land use/cover change with remote sensing data is often difficult. Also, differences in sun elevation angles and sun azimuth angles between the multitemporal images can cause serious problems in change detection because of the shadows cast by tall objects. Shadow sizes, shapes, and locations are changed by the different sun elevation angles and azimuth angles in different image acquisition dates, resulting in spurious change detection results. Shadows reduce the spectral values of true land covers 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 [45-48], these methods cannot completely extract shaded impervious surfaces from other land covers such as water because of their similar spectral signature. A simple but time-consuming method is to visually interpret the image and manually edit the shaded impervious surfaces, as used in this research, because human beings can comprehensively use color, shape, spatial patterns, the contextual information, along with their knowledge and experience to interpret different impervious surfaces and shaded areas in the high spatial resolution images [22].

High spatial resolution images often result in high spectral variation which induces misclassification or poor change detection. As this research shows, reducing the spectral variation can improve change detection performance, as the use of segmentation images. Selection of suitable textural images may improve change detection performance as well [49-53], because textures include the spatial information along the neighboring pixels.

5.2 Impacts of environmental conditions

In land use/cover change detection, it is important to maintain similar environmental conditions between the multitemporal images [23]. However, in practice, this is conditional to data availability. In urban land use/cover change detection, different moisture conditions can significantly affect the spectral signatures for the same impervious surface materials and affect the spectral differences between different impervious surface materials and other land covers such as bare soils and wetlands. Another important factor is potential seasonal differences in vegetation conditions. For example, on the June 20, 2008 QuickBird image, the crop residues or bare soils in the fields have similar spectral signatures with some impervious surface materials in visible and NIR bands, affecting change detection performance. The matched filtering method can reduce the impacts of external factors such as the atmospheric conditions and vegetation phenology between the multitemporal images. Thus, the use of classified impervious surfaces can improve change detection results by removing the impacts of external factors on the remote sensing data.

5.3 Selection of change detection algorithms

Selection of suitable techniques is important for improving change detection performance. Many factors can affect the selection of change detection techniques [2]. For very high spatial resolution images, the high spectral variation within the same land cover and the complexity of impervious surface materials will produce large change detection errors if per-pixel based change detection methods are used. As shown in this research, per-pixel based image differencing and PCA cannot effectively deal with the problem of high spectral variation within the same land cover, but segmentation-based methods can reduce this problem. Although PCA is an effective way to conduct change detection, the change information may be included in different PCs. No single PC contains all change information, thus, use of PCA often produces poor results. Both PCA and image differencing methods cannot deal with the spectral confusion among impervious surfaces, bare soils, wetland/water, crop residues, and shadows, however, the matched filtering method can reduce the impacts of non-impervious surfaces and the differences of impervious surfaces on different QuickBird images, and thus improve the change detection performance. For high spatial resolution images, more efforts should be on the development of object-based or textural-based methods for improving change detection performance [25-26, 54-55], in addition to the use of classified images as shown in this research.

6 CONCLUSIONS

Detection of urban expansion with very high spatial resolution images is challenging due to the impacts from remote sensing data per se, environmental conditions and the change detection algorithms used. This research indicates that the comparison of classified impervious surface images with the matched filtering method or segmentation-based image differencing method is recommended for urban expansion detection when very high spatial resolution images are used. Image differencing method based on per-pixel spectral signatures or PCA-based change detection methods are not suitable for urban change detection. This research indicates the importance of developing a stable variable from the remote sensing spectral signature when high spatial resolution data are used for urban change detection.

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