Extraction of urban impervious surfaces from an IKONOS image

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Impervious surface has been recognised as an important indicator in urban environmental assessment. However, accurate extraction of impervious surface information in urban areas is a challenge because of the complexity of impervious materials. This paper explores different approaches for impervious surface extraction with IKONOS imagery in Indianapolis, U.S.A., by using decision tree classifier (DTC) and linear spectral mixture analysis (LSMA). This research indicates that DTC is an effective approach for extraction of different impervious surface classes, including high-, medium- and low-reflectivity impervious surfaces and that LSMA-based approach can provide quantitative measure of imperviousness. A critical step is to separate dark impervious objects/features from shadows cast by tall buildings and tree canopy and from water.

1. Introduction

Impervious surface is generally defined as any materials that water cannot infiltrate and is primarily associated with human activities and habitation through construction of transportation and buildings (Slonecker et al. 2001, Bauer et al. 2004). Impervious surface has long been recognised 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 (Wu and Murray 2005, Lu et al. 2006), urban land use planning (Harbor 1994, Brabec et al. 2002) and urban environmental assessment (Weng et al. 2006). The latter focuses especially on water quality (Schueler 1994, Arnold and Gibbons 1996, Zug et al. 1999, Brabec et al. 2002), rainfall runoff (Weng 2001, Lohani et al. 2002) and urban heat island effect (Weng et al. 2004). Therefore, research on the extraction of impervious surfaces from remotely sensed data has attracted interest since the 1970s. Slonecker et al. (2001) reviewed various approaches to impervious surface extraction from remotely sensed data. Three basic categories (interpretative applications, spectral applications and modeling applications) were identified, which were based on the achievements in the 1970s and 1980s. Brabec et al. (2002) summarised four ways for estimating impervious surface, i.e. using a planimeter to measure impervious surface areas on an aerial photograph, counting the number of intersections on a grid overlain on an aerial photograph, conducting image

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classification and estimating impervious surface through the percentage of urbanisation in a region. During 1970s and 1980s, much research for impervious surface extraction was based on aerial photographs (Slonecker et al. 2001, Brabec et al. 2002). In the past decade, more research has been directed to developing advanced approaches for quantitative extraction of impervious surfaces from satellite images. These approaches include advanced per-pixel image classification (Hodgson et al. 2003, Dougherty et al. 2004, Jennings et al. 2004), sub-pixel classification (Ji and Jensen 1999, Civico et al. 2002, Phinn et al. 2002, Rashed et al. 2003) and decision tree modeling (Yang et al. 2003a, b, Goetz et al. 2004, Jantz et al. 2005). Extraction of impervious surfaces has also been conducted by the combination of high-albedo and low-albedo fraction images, which are developed by using a linear spectral mixture analysis of multispectral images (Wu and Murray 2003, Wu 2004, Lu and Weng 2006). An alternative for estimation of impervious surfaces is to establish relationship between impervious surfaces and vegetation cover (Gillies et al. 2003, Bauer et al. 2004).

Many previous studies in impervious surface estimation and mapping are based on the use of medium spatial resolution images such as Landsat Thematic Mapper/Enhanced Thematic Mapper Plus (TM/ETM+) images (Wu and Murray 2003, Yang et al. 2003a, Lu and Weng 2006). However, the medium resolution is often regarded as too coarse for use in urban areas because of the heterogeneity in the urban landscape and the complexity of urban impervious surface materials (Jensen and Cowen 1999, Lu and Weng 2004). Although sub-pixel-based approaches for extraction of impervious surfaces can improve accuracy of the extracted image (Wu 2004, Lu and Weng 2006), the impervious surface is often overestimated in the less-developed areas, such as low-intensity residential areas, because bright impervious objects often exaggerate their proportion in spectral features in the mixed pixels. In contrast, the impervious surface is underestimated in the well-developed areas, such as high intensity residential areas, because similar spectral responses between some bright impervious surfaces and dry soils create confusion (Lu and Weng 2006). As high spatial resolution images, such as IKONOS and QuickBird, are readily available, use of the high spatial resolution images for extraction of impervious surface has attracted increasing attention (Cablk and Minor 2003, Goetz et al. 2003). However, the shadows from tall buildings or large tree crowns in the high spatial resolution imagery become a severe problem for extracting impervious surfaces. The confusion in spectral responses between dark impervious surface areas, water and shadows also creates difficulty.

To date, an effective approach to extracting urban impervious surface areas from high spatial resolution images is not available. Hence, this paper aims to explore methods for extraction of impervious surface area with an IKONOS image in the urban area of Indianapolis, United States. Specifically, the first objective is to explore a suitable approach to extract impervious surface based on spectral features. A decision tree classifier is used. As a comparison, a maximum likelihood classifier is also used to classify impervious surfaces. The second objective is to extract a continuous impervious surface image with a linear spectral mixture analysis.

2. Methods

2.1 Study area and datasets

A typical urban area in Indianapolis, Indiana, U.S.A., was selected for this study. Different urban land uses, such as commercial use, different intensities of residential
use, forest, grass and rivers can be found in this study area. It is an ideal area for a research on extraction of urban impervious surface areas. Due to the complexity of urban environments, it has proven difficult to extract impervious surface especially in less developed areas, using medium spatial resolution images, such as Landsat TM images (Lu and Weng 2006). High spatial resolution images, such as IKONOS with 4 m spatial resolution in four bands in blue, green, red and near infrared spectrum and with 1-m resolution in the panchromatic band, can significantly reduce the mixed pixel problem. Hence, an IKONOS multispectral image was used in this research. This cloud-free IKONOS image was acquired on 6 October 2003.

2.2 Analysis of spectral features

The urban landscape is a complex assemblage which is composed of different materials, such as grass, trees, water and different kinds of impervious surface materials (Jensen 2000). Different impervious objects have different spectral characteristics. For example, building roofs with bright or white colour have high reflectance in visible, near-infrared (NIR) and shortwave infrared (SWIR) wavelengths; conversely, roads or building roofs with dark colours can absorb most of the solar energy, resulting in very low surface reflectance in the visible, NIR and SWIR bands. Therefore, bright impervious surfaces appear white, while dark impervious surfaces appear dark gray to black on the IKONOS colour composite image (assigning IKONOS bands 4, 3 and 2 as red, green and blue). Based on different spectral responses, low-, medium- and high-reflectivity impervious surface (LRIS, MRIS and HRIS) classes can be identified. LRIS is defined as dark impervious objects with low reflectance, especially in visible and near-infrared bands, thus LRIS objects appear as dark grey to black in the colour composite image. HRIS is defined as impervious objects with high reflectance, thus appearing as white in the colour composite. MRIS is defined as impervious objects having reflectance values between LRIS and HRIS. Some land covers, such as impervious surface and vegetation, have significantly different colours, while other land covers, such as dark impervious surface, water bodies and shadows cast by buildings or tree canopy have similar colours on the IKONOS colour composite.

Previous research has shown the difficulty in separating dark impervious surfaces from water and shadows based on spectral signatures with traditional classification algorithms such as the maximum likelihood classifier (Lu and Weng 2004, 2005). In order to analyse their spectral features, typical sample plots were selected based on visual interpretation of the IKONOS colour composite. Approximately 10 sample plots with window sizes of 5 × 5 pixels for each selected land-cover class were identified on the IKONOS image. Figure 1 gives a comparison of mean spectral values among different impervious surfaces and other land-cover classes based on the selected sample plots. HRIS and MRIS have spectral features substantially different from other land covers and can thus be separated directly from visible bands (figure 1(a)). Forest and grass have different spectral features in near-infrared (NIR) bands and can be directly separated from other land covers based on NIR band or normalised difference vegetation index (NDVI) image. Figure 1(b) illustrates the land-cover classes with low spectral values. The LRIS has higher spectral signatures, especially in the NIR band, than water and building-cast shadows. The tree crown-cast shadows have different features in NIR or NDVI compared with other low spectral feature classes and can be separated based on NIR
Figure 1. A comparison of mean spectral values for different land-cover classes on the IKONOS image (the wavelength unit is μm): (a) three impervious surface classes with different levels of spectral values, grass, forest and water; (b) a comparison of shadows and land covers with low spectral values.
or NDVI. The difficulty is the separation of water from building-cast shadows. The
analysis of spectral features of different impervious surfaces provides the
fundamental information for discriminating between them.

A suitable classification scheme is required for discriminating various impervious
surface classes with other land cover types in urban areas. Impervious surface
can be regarded as non-shadowed and shadowed types. The non-shadowed
impervious surface can be classified into HRIS, MRIS and LRIS based on spectral
signatures. The shadowed impervious surface has a similar spectral signature to
water and LRIS. As this study focuses on the extraction of impervious surface,
we grouped grass and forest as a vegetation category. Two classification systems
were used. One system consisted of HRIS, MRIS, LRIS, shadowed impervious
surface, vegetation and water, which emphasised the spectral features of different
types of impervious surfaces. Another system consisted of impervious surface (i.e.
assigning HRIS, MRIS, LRIS and shadowed impervious surface as one class),
vegetation and water only, without considering the differences among various
impervious materials.

2.3 Impervious surface extraction with classification methods

The selection of a suitable classification approach is important in order to achieve
desired classification results. In previous research different classification appro-
aches, such as maximum likelihood classifier (MLC) (Fankhauser 1999) and
decision tree classifier (DTC) (Goetz et al. 2003, Yang et al. 2003a) have been used
for the extraction of impervious surface areas. The MLC is a parametric classifier
that assumes normal distribution for each feature of interest, associated with an
equal prior probability among the classes. Hence, insufficient training samples or
non-representativeness of features of interest or having multimodal data distribution
are often linked to poor classification results, because of inaccurate estimation of the
mean vector and covariance matrix used in the MLC algorithm. In urban areas, the
assumption of normal distribution is often violated and selection of training sample
plots is difficult because of the complex urban environments. Much previous
research has indicated that nonparametric classifiers provide better classification
results than parametric classifiers in complex landscapes (Foody 2002a).
Nonparametric classifiers, such as DTC and neural networks, have received
increasing interest in urban land-cover classification. Hence, DTC was used in this
research for extraction of impervious surfaces. Detailed descriptions of DTC can
be found in previous literature (Friedl and Brodley 1997, Pal and Mather 2003,
Yang et al. 2003b).

The procedure for extraction of impervious surface areas is illustrated in Figure 2.
A DTC was used to classify the IKONOS image into three reflectance levels of
impervious surface. NDVI was used to separate vegetation from non-vegetation
class. The visible bands were used to separate HRIS and MRIS from other land
covers and NIR band used to separate LRIS from other land covers. Some LRIS,
water and shadows were confused and cannot be directly classified with the DTC
approach. Therefore, the spectral signatures of these confused pixels were extracted
and an unsupervised ISODATA method was applied to classify the spectral
signatures into 30 clusters. The clusters were merged into shadowed impervious
surface, LRIS, water and shadowed vegetation, based on the visual interpretation of
the classified image overlain on the IKONOS colour composite. Finally, HRIS,
MRIS, LRIS, shadowed impervious surface, vegetation and water were combined
into a thematic image. As a comparison, MLC was also conducted to classify the IKONOS image into a thematic map based on the selected training samples.

### 2.4 Impervious surface extraction with linear spectral mixture analysis

Linear spectral mixture analysis (LSMA) is a physically based image processing tool which supports repeatable and accurate extraction of quantitative sub-pixel information (Smith et al. 1990). In the LSMA approach, one critical step is to select suitable endmembers. Much previous literature has detailed the LSMA approach and summarised the approaches for endmember selection (Adams et al. 1995, Theseira et al. 2003). Image endmembers can be derived from the extremes of the image feature space and represent the purest pixels in the images (Mustard and Sunshine 1999). In order to more effectively identify the image endmembers with high quality, different methods of image transformation, such as principal component analysis (PCA) and minimum noise fraction (MNF), are often used to transform the multispectral image into a new data set (Green et al. 1988, Boardman and Kruse 1994). The endmembers are then selected from the feature space of the transformed image (van der Meer and de Jong 2000, Small 2001, Wu and Murray 2003). In this research, three endmembers: high-albedo, low-albedo and vegetation were selected from the feature space of MNF components. A constrained least-squares solution was used to unmix the four IKONOS bands into fraction images.
Figure 3 illustrates the result of the spectral unmixing. The low-albedo fraction image highlighted land covers with low spectral reflectance, such as water, shadows and dark impervious surface areas, while high-albedo fraction image corresponded to land covers with high spectral reflectance, including bright impervious surface areas such as roads and building roofs. The vegetation fraction image mainly corresponded to forest and grass.

Dark impervious objects, water and building-cast shadows were similar in terms of image fraction values. They possessed high values in the low-albedo fraction, but low values in the vegetation and high-albedo fractions. In the vegetation fraction...
image, tree crown-cast shadows had higher values than building-cast shadows as well as dark impervious objects. Dark impervious objects were difficult to separate from water or building-cast shadows because of their highly similar fraction values in the three fraction images. It is necessary to apply additional steps to separate them. The pixels with dark impervious objects, water and shadows were selected if the low-albedo value was greater than threshold t1 and the high-albedo or vegetation fraction value was less than threshold t2. An unsupervised ISODATA approach was applied to these pixels. The confused classes of dark impervious surface, shadowed impervious surface and water were finally separated based on visual analysis of the classified image overlain on the IKONOS colour composite. After dark and shadowed impervious surfaces were extracted from the low-albedo fraction image, these were added to the high-albedo fraction images to develop an impervious surface fraction image with values of impervious surface fraction ranging from 0 to 1. In order to more effectively interpret the distribution of impervious surfaces, the derived impervious surface image was reclassified into three categories: high-, medium- and low-impervious surface, with values greater than 0.9, between 0.5 and 0.9 and less than 0.5, respectively. It should be noted that the classification images from DTC and LSMA were not comparable. The DTC-based impervious surface image was based on the differences in spectral responses among different impervious materials, with each pixel being placed in a particular class, while the LSMA-based impervious surface image was based on the proportion of imperviousness within a pixel.

### 2.5 Accuracy assessment

Accuracy assessment is an important part in the image classification. Different elements for accuracy assessment, such as overall accuracy (OA), producer’s and user’s accuracy (PA and UA) and kappa coefficient can be used and they can be calculated from an error matrix. Much previous literature has detailed the approaches for accuracy assessment (Congalton 1991, Smits et al. 1999, Foody 2002b). In order to compare the impervious surface images, the derived images based on MLC, DTC and LSMA, were regrouped into three classes: impervious surface, water and vegetation. In this study, a total of 150 sample plots with a window size of $3 \times 3$ pixels were randomly selected for accuracy assessment. The land cover class for each sample plot was visually interpreted on the colour composite of IKONOS bands 4, 3 and 2. An error matrix was then calculated for each classifier. Finally, PA and UA for each class, OA and kappa for each classifier were calculated based on the error matrix.

### 3. Results

The DTC provided significantly better classification performance than MLC. The overall accuracy in DTC was 92% compared with 79% in MLC (Table 1). The adjacent classes – HRIS, MRIS and LRIS were highly misclassified in MLC. Also tree-cast shadows were confused with LRIS, building-cast shadows and water, because the subtle differences in spectral signatures cannot effectively separate each other with the MLC. An obvious error in the MLC classification image was that some water areas were misclassified as building-cast shadows and MRIS areas were underestimated, as shown in figure 4(a). This misclassification was much reduced with the use of DTC, as shown in table 1 and figure 4(b).
The capacity of the LSMA-based approach to extract a quantitative measure of impervious surface has been demonstrated (see figure 5). The trend of impervious surface changes is obvious, from highest values in commercial areas, to medium values in residential areas and to the lowest values in non-urban regions (see figure 5). The majority of impervious surface pixels had values of greater than 0.9, as shown in the right image of figure 5. A small number of pixels with values less than 0.9 were located in residential areas and parks because of the mixture of roads, buildings, trees and grass. The LSMA-based approach has also showed the advantage of extracting sub-pixel impervious surface information from remotely sensed data. This capability is especially important when using medium or coarse spatial resolution images because of the mixed pixel problem (Lu and Weng 2006).

If non-shadow and shadowed impervious surfaces were considered as one class, both DTC and LSMA approaches provided similar accuracy and both had a higher accuracy than the MLC approach (see table 2). In the MLC approach, water was confused with dark or shadowed impervious surface. With the DTC or LSMA approach, this confusion was significantly reduced. The producer’s and user’s accuracies for impervious surface class for both DTC and LSMA approaches were between 96.5–97.6%. This indicated that the impervious surface images developed using DTC or LSMA were accurate and can be used for reference data for assessment of the results from medium or coarse spatial resolution images. A comparison of figures 4 and 5 indicated that some mixed pixels composed of impervious surface and other land-cover classes can be extracted using the LSMA-based approach, which provided more accurate results for such areas as lower density residential regions.

4. Discussion

Previous research has shown that non-parametric classifiers may provide better classification accuracy than parametric classifiers in urban environments. The

<table>
<thead>
<tr>
<th>Method</th>
<th>Type</th>
<th>HRIS</th>
<th>MRIS</th>
<th>LRIS</th>
<th>Shad</th>
<th>WAT</th>
<th>VEG</th>
<th>PA(%)</th>
<th>UA(%)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>HRIS</td>
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<td>5</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>100</td>
<td>57.7</td>
<td>OA(%) : 79.3%</td>
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<tr>
<td></td>
<td>MRIS</td>
<td>27</td>
<td>4</td>
<td></td>
<td>1</td>
<td></td>
<td>81.8</td>
<td>84.4</td>
<td>Kappa: 79.3%</td>
</tr>
<tr>
<td></td>
<td>LRIS</td>
<td>1</td>
<td>9</td>
<td>1</td>
<td></td>
<td></td>
<td>42.9</td>
<td>81.8</td>
<td>Kappa: 79.3%</td>
</tr>
<tr>
<td></td>
<td>Shad</td>
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<td>11</td>
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<td></td>
<td></td>
<td>64.7</td>
<td>84.6</td>
<td>0.74</td>
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<td></td>
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<td></td>
<td></td>
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<td>76.5</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td></td>
<td>VEG</td>
<td>5</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>44</td>
<td>93.6</td>
<td>80.0</td>
<td></td>
</tr>
<tr>
<td>DTC</td>
<td>HRIS</td>
<td>15</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>100</td>
<td>100</td>
<td>OA(%) :</td>
</tr>
<tr>
<td></td>
<td>MRIS</td>
<td>30</td>
<td>2</td>
<td></td>
<td>1</td>
<td></td>
<td>90.9</td>
<td>90.9</td>
<td>92.0%</td>
</tr>
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<td>80.9</td>
<td>77.3</td>
<td>Kappa: 92.0%</td>
</tr>
<tr>
<td></td>
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<td></td>
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<td>88.2</td>
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<td>0.90</td>
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<tr>
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<td>94.1</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td></td>
<td>VEG</td>
<td>2</td>
<td>1</td>
<td>45</td>
<td>4</td>
<td></td>
<td>95.7</td>
<td>93.8</td>
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</table>

Note: HRIS, MRIS and LRIS represent high-, medium- and low-reflectivity impervious surface; Shad represents shadowed impervious surface; WAT represents open water bodies; and VEG represents vegetation, including forest, tree-cast shadows and grass.

PA, UA, OA and Kappa represent producers’ accuracy, user’s accuracy, overall classification accuracy and kappa coefficient.

MLC and DTC represent maximum likelihood classifier and decision tree classifier.

Row represents the reference data and column represents the classification results.
present research confirms that this conclusion also applies to high spatial resolution images. It has been shown in this paper that misclassification is mainly owing to lack of clear boundary between the adjacent levels of HRIS, MRIS and LRIS and similar spectral signatures among water, shadows and LRIS. The complex urban landscape often violates the normal distribution assumption used in MLC algorithm, resulting in large misclassification. On the contrary, the DTC approach does not use the mean and covariance which is derived from the training sample plots and does not require the normal distribution, thus the DTC approach provides better classification accuracy than the MLC. As shown in this paper, the above confusions are considerably reduced through the combined use of DTC and unsupervised ISODATA approaches because of the use of specific rules in DTC and the further processing and expert knowledge used to deal with the confusion between shadows and water.

This research has shown the difficulty in distinguishing between the classes of water, shadows and dark impervious objects. To date, there is no effective approach to separate these classes based on spectral features. As spatial resolution increases,
Figure 5. Impervious surface images developed from the linear spectral mixture analysis: (a) impervious surface images with values ranging from 0 (black) to 1 (white); (b) three levels of impervious surface image illustrating some mixed pixels in residential areas or border between impervious surface and other land covers.
(Note: high-, medium- and low-impervious surface classes are regrouped based on the proportion of impervious value in a pixel, i.e. values greater than 0.9, between 0.5 and 0.9 and less than 0.5)

Table 2. Comparison of different approaches for extracting impervious surface areas.

<table>
<thead>
<tr>
<th>Method</th>
<th>Type</th>
<th>ISA</th>
<th>WAT</th>
<th>VEG</th>
<th>PA(%)</th>
<th>UA(%)</th>
<th>OA(%)</th>
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<tbody>
<tr>
<td>MLC</td>
<td>ISA</td>
<td>77</td>
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<td>93.9</td>
<td>89.5</td>
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</tr>
<tr>
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<td>13</td>
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<td>100.0</td>
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<tr>
<td></td>
<td>VEG</td>
<td>9</td>
<td>2</td>
<td>44</td>
<td>80.0</td>
<td>93.6</td>
<td></td>
</tr>
<tr>
<td>DTC</td>
<td>ISA</td>
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</tr>
<tr>
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<td>WAT</td>
<td>16</td>
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<td>100.0</td>
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<tr>
<td></td>
<td>VEG</td>
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<td>45</td>
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<td>LSMA</td>
<td>ISA</td>
<td>83</td>
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<td>1</td>
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<tr>
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<td>VEG</td>
<td>3</td>
<td>46</td>
<td></td>
<td>93.9</td>
<td>97.9</td>
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</tr>
</tbody>
</table>

Note: ISA, WAT and VEG represent impervious surface areas, water and vegetation. PA, UA and OA represent producers’ accuracy, user’s accuracy and overall classification accuracy. MLC, DTC and LSMA represent maximum likelihood classifier, decision tree classifier and linear spectral mixture analysis. The numbers in row represents the reference data and in column represents the classification results.
the shadows cast by tall buildings or tree crowns became a serious problem. No approaches are available for effectively removing the shadow impacts. The impact of shadows also affects the extraction of impervious surface areas. In medium spatial resolution images, such as those of Landsat TM/ETM+ and Terra ASTER, the use of a thermal band has been proven to be an effective way to separate dark impervious surface from water, shadowed impervious surface areas and shadows in the vegetated areas (Lu and Weng 2006). However, high spatial resolution image sensors usually do not contain a thermal band and have limited number of spectral bands. This research uses unsupervised classification to separate dark impervious surface, water and shadows, as an image analyst can effectively use his/her knowledge of the study area in merging spectral clusters into information classes. Another problem with high spatial resolution images is the increased spectral variation within the same land-cover. Thus, a per-pixel-based approach is often found unsuitable for the classification of high spatial resolution images. Use of textures or object-orientation classification may benefit the land cover classification (Lu and Weng 2005).

The classified images based on DTC and LSMA have their own merits and may have different usages. For example, the DTC-based classification image (see figure 4(b)) provides the distribution of impervious surfaces with different reflectance values, implying the spatial distribution of different kinds of impervious materials, such as dark-coloured or bright-coloured construction materials used in roads and building roofs. This information is useful for examining the relationships between different impervious materials and their land surface temperature. On the other hand, figure 5 provides continuous values of impervious surface in a pixel, especially for those mixed pixels along the borders between impervious surface and other land-covers. The LSMA-based approach provides more accurate impervious surface estimation when medium or coarse spatial resolution images are used (Lu and Weng 2006). The quantitative variable resulting from this approach is especially valuable when the impervious surface data are used as an input for development of models for environmental evaluations.

5. Conclusions

High spatial resolution images such as IKONOS are an important data source for estimating and mapping urban impervious surface areas. One critical step is to extract dark impervious surface areas and shadowed impervious surfaces, which are often confused with water and shadows cast by tree crowns. This study demonstrates that a hybrid approach based on a decision tree classifier and an unsupervised ISODATA classifier can effectively extract impervious surface areas. The hybrid approach provided significantly better results than a maximum likelihood classifier. The LSMA-based approach can provide a quantitative measure of imperviousness, which is especially significant if impervious surface data are used for inputs into environmental modelling and estimation.

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