Mapping Impervious Surface Distribution with the Integration of Landsat TM and QuickBird Images in a Complex Urban–Rural Frontier in Brazil

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13.1 INTRODUCTION

Impervious surfaces are generally defined as any man-made materials that water cannot infiltrate. They are primarily associated with human activities and habitation through the construction of transportation infrastructure and buildings (Slonecker et al. 2001; Bauer et al. 2008). Impervious surface area (ISA) has long been recognized as an important factor in many urban or environment related studies, including the improvement of urban land use and land cover (LULC) classification (Madhavan et al. 2001; Phinn et al. 2002; Lu and Weng 2006a), 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, especially water quality (Schueler 1994; Arnold and Gibbons 1996; Zug et al. 1999; Brabec et al. 2002) and rainfall runoff (Lohani et al. 2002). Therefore, the timely and accurately mapping ISA distribution is of importance. The unique characteristics of remote sensing data in repetitive data acquisition, its synoptic view, and digital format suitable for computer processing make it the primary data source for ISA mapping. The research for extracting ISA from remotely sensed data has attracted great attention since the 1970s, especially in the most recent decade (Phinn et al. 2002; Gillies et al. 2003; Wu and Murray 2003; Yang et al. 2003a; Lu and Weng 2006a; Bauer et al. 2008; Mohapatra and Wu 2008; Wang et al. 2008; Xian et al. 2008; Hu and Weng 2009; Wu 2009; Weng et al., 2009; Yang et al. 2010). Since many new techniques for ISA mapping have been developed in recent decades, it is necessary to overview recent progress in order to provide guidelines for selecting a suitable technique for a specific study. This chapter briefly summarizes the major ISA mapping techniques that have appeared in recent literature and then provides a case study of ISA mapping with the integrated use of Landsat Thematic Mapper (TM) and QuickBird images in a complex urban–rural frontier in Brazil.

13.2 BACKGROUND

Urban landscapes can be regarded as a complex combination of buildings, roads, grass, trees, soil, water, and so on. In high spatial resolution images such as QuickBird and IKONOS, individual objects such as buildings and roads can be clearly identified; however, these features are less distinct in Landsat TM color composites because of Landsat’s relatively coarse spatial resolution (i.e., 30 m; see Figure 13.1). Different construction materials often result in high spectral variation, that is, different ISA appears complex colors in QuickBird image, making it difficult to automatically map ISA distribution based on spectral signatures. In coarse and medium spatial resolution images such as Landsat TM, mixed pixels can be a serious problem, diminishing the effective use of remotely sensed data in urban LULC classification and change detection. If per-pixel based methods are used for mapping urban LULC distribution based on medium or coarse spatial resolution images, large uncertainty may be introduced into the result, that is, urban ISA extent could be significantly overestimated, and ISA in rural areas could be significantly underestimated (Lu and Weng 2004). This situation worsens if multitemporal remote sensing data are used for urban LULC change detection, especially in the urban–rural frontiers.
In urban environments, land covers are assumed to be a linear combination of three components: vegetation, ISA, and soil (V-I-S) (Ridd 1995). The V-I-S model provides a guideline for decomposing urban landscapes and a link for these components to remote sensing spectral characteristics. Several studies have adopted this model as a basis for understanding the urban environment (Ward et al. 2000; Madhavan et al. 2001; Rashed et al. 2001; Phinn et al. 2002). From the view of remote sensing data, shade is also an important part affecting the spectral signature. Therefore, shade, green vegetation, soil, and ISA can almost explain all land covers in urban landscape (Lu and Weng 2004). In practice, ISA has high spectral variation; for example, bright building roofs may have very high spectral signatures that are confused with soils; dark roads and building roofs have very low spectral signatures that are often confused with shadow, water, and wetland (see Figure 13.1). Thus, direct extraction of ISA from remotely sensed data becomes very difficult because of the spectral confusion between ISA and other land covers. We can assume that urban landscape is composed of four components: high-albedo land covers, low-albedo land covers, vegetation, and soil. All land covers are a composition of these four components with linear or nonlinear relationship. Previous research has indicated that these four fraction images can be developed with spectral mixture analysis (Wu and Murray 2003; Lu and Weng 2006a,b). High-albedo fraction image highlights the land covers with high spectral reflectance, such as bright ISA and dry bare soils; low-albedo fraction image highlights the land cover with low spectral reflectance, such as dark ISA, shadow, water, and wetland. Soil fraction image highlights soil information, mainly located in agricultural lands; vegetation fraction image highlights the

**FIGURE 13.1** Comparison of color composites between QuickBird (left) and TM images (right), illustrating the mixed pixel problem in relatively coarse spatial resolution image.
forest and plantation information. ISA is mainly concentrated on the high- and low-
albedo fraction images; thus, ISA can be extracted from the addition of high- and 
low-albedo fraction images (Wu and Murray 2003; Lu and Weng 2006a,b).

Since the 1970s, many approaches for ISA mapping have been developed. Based on 
the achievements in the 1970s and 1980s, Slonecker et al. (2001) reviewed many of the 
approaches for ISA extraction from remotely sensed data and grouped them into three 
basic categories: interpretive applications, spectral applications, and modeling applica-
tions. Brabec et al. (2002) summarized four ways for ISA mapping: (1) using a planim-
eter to measure ISA on aerial photography, (2) counting the number of intersections 
on the overlain grid on an aerial photography, (3) conducting image classification, and 
(4) estimating ISA through the percentage of urbanization in a region. Recently, more 
advanced algorithms have been developed for quantitative extraction of ISA from satel-
lite imagery. The major methods include per-pixel image classification (Lu and Weng 
2009), subpixel classification (Ji and Jensen 1999; Phinn et al. 2002; Rashed et al. 2003), 
near network (Mohapatra and Wu 2008; Wang et al. 2008; Hu and Weng 2009; Wu 
2009), regression tree model (Yang et al. 2003a,b; Xian and Crane 2005; Xian 2008; 
Xian et al. 2008; Yang et al. 2009), the combination of high-albedo and low-albedo 
fraction images (Wu and Murray 2003; Wu 2004; Lu and Weng 2006a,b; Weng et al. 
2008, 2009), and through the established relationship between ISA and vegetation cover 
(Gillies et al. 2003; Bauer et al. 2008). Major ISA mapping approaches can be summa-
ized based on satellite images, which have appeared in recent literature (Table 13.1).

Image classification-based methods for mapping ISA are common (Slonecker et 
al. 2001; Brabec et al. 2002), but overestimation often occurs in urban extent and 
underestimation occurs in rural landscapes due to the limitation of spatial resolution 
in remotely sensed data and the heterogeneity in the urban environment (Lu 
and Weng 2004). The high spectral variation in ISA and similar spectral signatures 
between ISA and other nonvegetation land covers also make it difficult to select suit-
able training samples for the ISA class, resulting in misclassification. An alternative 
is to use ERDAS IMAGINE’s subpixel classifier (Ji and Jensen 1999; Civco et al. 
2002). However, the complexity of ISA materials often makes the subpixel classi-
fier difficult to employ and leads to underestimation in ISA extraction. Since a high 
inverse correlation exists between vegetation cover and ISA in urban landscapes, the 
ISA can be estimated based on the established regression models with the vegeta-
tion indices, such as from tasseled cap greenness (Bauer et al. 2008) and fractional 
vegetation cover from the normalized difference vegetation index (NDVI) (Gillies 
et al. 2003). This approach has a drawback in that vegetation greenness varies with 
different seasons, which may result in large uncertainties of ISA estimation. Also 
this method cannot be directly transferred to other study areas or other dates of data 
sets due to local specificities regarding phenologies, climate conditions, and differ-
ent composition of land covers in the urban landscape. Another common method for 
ISA estimation is based on the regression tree model (Yang et al. 2003a,b; Xian and 
Crane 2005; Xian 2008; Xian et al. 2008; Yang et al. 2009), which has been used for 
ISA mapping for continental United States based on Landsat TM images.

In recent years, spectral mixture analysis (SMA) has emerged as an important 
approach for ISA extraction from multispectral data. For example, ISA as one of the 
endmembers may be directly extracted from remotely sensed data (Rashed et al.
TABLE 13.1
Summary of Major Approaches for Impervious Surface Mapping

<table>
<thead>
<tr>
<th>Category</th>
<th>Approach</th>
<th>Materials</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per-pixel based methods</td>
<td>Decision tree classifier, maximum likelihood</td>
<td>IKONOS, QuickBird</td>
<td>Goetz et al. 2003; Lu and Weng 2009; Lu et al. 2011</td>
</tr>
<tr>
<td>Subpixel based methods</td>
<td>Subpixel classifier</td>
<td>TM</td>
<td>Ji and Jensen, 1999</td>
</tr>
<tr>
<td></td>
<td>Artificial neural networks</td>
<td>ASTER</td>
<td>Hu and Weng, 2009</td>
</tr>
<tr>
<td></td>
<td>Subpixel proportional land cover information</td>
<td>TM, videography</td>
<td>Wang and Zhang, 2004</td>
</tr>
<tr>
<td></td>
<td>transformation (SPLIT)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard SMA</td>
<td>IRS-1C; TM</td>
<td>Rashed et al., 2001; Phinn et al., 2002</td>
</tr>
<tr>
<td></td>
<td>Addition of low- and high-albedo fractions</td>
<td>ETM+</td>
<td>Wu and Murray, 2003; Wu, 2004</td>
</tr>
<tr>
<td></td>
<td>derived from standard or normalized SMA</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Modified approach based on low-albedo, high-albedo, and land surface temperature</td>
<td>ETM+</td>
<td>Lu and Weng, 2006a, b</td>
</tr>
<tr>
<td></td>
<td>Multiple endmember SMA</td>
<td>TM</td>
<td>Rashed et al., 2003</td>
</tr>
<tr>
<td></td>
<td>Combination of support vector machines and geospatial analysis</td>
<td>ETM+, ATKIS vector data</td>
<td>Esch et al., 2009</td>
</tr>
<tr>
<td></td>
<td>Regression tree model</td>
<td>ETM+</td>
<td>Xian and Crane 2005; Yang et al., 2003a, b</td>
</tr>
<tr>
<td></td>
<td>Multiple regression analysis</td>
<td>DMSP-OLS, ancillary data</td>
<td>Elvidge et al., 2007; Sutton et al., 2009</td>
</tr>
<tr>
<td>Vegetation-based methods</td>
<td>A regression model based on impervious surface and tasseled cap greenness</td>
<td>TM</td>
<td>Bauer et al., 2008</td>
</tr>
<tr>
<td></td>
<td>Based on fraction vegetation cover (Fr), i.e., 1-Fr for the developed areas</td>
<td>MSS and TM</td>
<td>Gillies et al., 2003</td>
</tr>
<tr>
<td>Other methods</td>
<td>A combination of image processing methods based on PCA and spatial morphological operators</td>
<td>IKONOS</td>
<td>Cablk and Minor, 2003</td>
</tr>
<tr>
<td></td>
<td>Combination of knowledge-based classification and spectral unmixing</td>
<td>MSS/TM/ETM+</td>
<td>Powell et al., 2008</td>
</tr>
</tbody>
</table>

2001; Phinn et al. 2002). ISA estimation may be improved by the addition of high- and low-albedo fraction images, which both are used as endmembers in SMA (Wu and Murray 2003; Lu and Weng 2006a,b). In addition, multiple endmember SMA (MESMA) (Rashed et al. 2003) has also been applied in which several ISA endmembers can be extracted. However, ISA is often overestimated or underestimated when medium spatial resolution images are used, depending on the relative proportion of
ISA in a pixel (Wu and Murray 2003; Lu and Weng 2006a,b; Greenfield et al. 2009). Since high spatial resolution satellite images (e.g., IKONOS and QuickBird) have become available, more research has shifted to the use of these data (Mohapatra and Wu 2008; Lu and Weng 2009; Wu 2009; Lu et al. 2011). However, the use of high spatial resolution images also presents a challenge for automatically mapping ISA distribution (Lu and Weng 2009). The main problems include spectral confusion between ISA and other land covers due to limited spectral resolution [i.e., usually only visible and near-infrared (NIR) wavelengths are available in very high spatial resolution images], high spectral variation within the same land cover, and shadows caused by tall objects and the confusion between dark ISA and water/wetland (Dare 2005; Li et al. 2005; Chen et al. 2007; Zhou et al. 2009).

13.3 RESEARCH PROBLEMS AND OBJECTIVES

In a complex urban–rural landscape, traditional classification methods cannot effectively distinguish ISA from other land covers due to the spectral confusion between dark ISA and wetland/water. A similar issue happens among bright ISA, soils, and cropped fields. Sometimes, traditional classification methods cannot effectively distinguish ISA from other land covers due to the difficulty in selecting training sample plots. Although subpixel-based methods can improve area estimation accuracy, it is critical and often difficult to distinguish the pixels with ISA from other land covers. Rarely has research focused on the improvement of ISA estimation in a complex urban–rural environment with multiscale remote sensing data. Therefore, this case study attempts to develop a new method suitable for a complex urban–rural landscape for mapping ISA distribution with the combination of Landsat TM and QuickBird images.

13.4 DESCRIPTION OF THE STUDY AREA

The city of Lucas do Rio Verde (hereafter called Lucas) in Mato Grosso State, Brazil, has a relatively short history and small urban extent (see Figure 13.2). It was established in 1982 and has experienced rapid urbanization. Highway BR 163 connects Lucas in the north to Santarém, a river port city on the Amazon River, and in the south to the heart of the soybean growing area at Cuiabá, capital city of Mato Grosso state. Highway BR-163 is a major route for the transport of export bound commodities grown in the region. The economic base of Lucas is large-scale 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 are developing as are other industrial complexes to add value to the agricultural output, which is now substantial. The county is at the epicenter of soybean production in Brazil, and it is expected to grow in population threefold in the next 10 years (personal communication with secretariat for planning at Lucas). Because this relatively small town has complex urban–rural spatial patterns derived from its highly capitalized agricultural base, large silos and warehouses, and planned urban growth, Lucas is an ideal site for exploring the methods for rapidly mapping urban extent with remotely sensed data.
13.5 METHODOLOGY

Mapping ISA with Landsat images in a complex urban–rural frontier is challenging due to the mixed pixel problem and the confusion of ISA with other land covers. This research designed a comprehensive method based on the combined use of QuickBird and Landsat images, as illustrated in Figure 13.3. The major steps include: (1) mapping ISA with a hybrid method based on QuickBird imagery, (2) extracting per-pixel ISA images from Landsat images based on the thresholding of maximum and minimum filtering images and unsupervised classification, (3) mapping fractional images of high-albedo, low-albedo, vegetation, and soil endmembers with linear spectral mixture analysis, and (4) evaluation and calibration of the Landsat-derived impervious surface image.

FIGURE 13.3 Strategy of integrating Landsat TM and QuickBird images for mapping impervious surface distribution.
mixture analysis (LSMA), and producing a fractional ISA image by adding high-albedo and low-albedo fraction images while removing non-ISA pixels by combining the per-pixel ISA image from step 2, and (4) establishing a regression model to calibrate the Landsat-derived ISA by using the QuickBird-derived ISA imagery.

13.5.1 IMAGE PREPROCESSING

A Landsat TM image acquired on May 22, 2008 and a QuickBird image acquired on June 20, 2008 were used in this research. The TM image was geometrically registered into a Universal Transverse Mercator (UTM) projection with geometric error of less than 0.5 pixel. The nearest neighbor resampling method was used to resample the Landsat image into a pixel size of 30 m by 30 m during image-to-image registration. Radiometric and atmospheric correction was conducted on the TM image by utilizing the dark object subtraction (DOS) approach. The DOS model is an image-based procedure that standardizes imagery for the effects caused by solar zenith angle, solar radiance, and atmospheric scattering (Lu et al. 2002; Chander et al. 2009). Here are the equations used for Landsat image calibration:

\[ R_\lambda = PI \cdot D \cdot (L_\lambda - L_{\text{haze}})/(Esun_\lambda \cdot \cos(\theta)) \] (13.1)

\[ L_\lambda = \text{gain}_\lambda \cdot DN_\lambda + \text{bias}_\lambda \] (13.2)

where \( L_\lambda \) is the apparent at-satellite radiance for spectral band \( \lambda \), \( DN_\lambda \) is the digital number of spectral band \( \lambda \), \( R_\lambda \) is the calibrated reflectance, \( L_{\lambda\text{haze}} \) is path radiance, \( Esun_\lambda \) is exoatmospheric solar irradiance, \( D \) is the distance between the Earth and Sun, and \( \theta \) is the Sun zenith angle. The path radiance for each band is identified based on the analysis of water bodies and shades in the images. The \( \text{gain}_\lambda \) and \( \text{bias}_\lambda \) are radiometric gain and bias corresponding to spectral band \( \lambda \), respectively, and they are often provided in an image head file or metadata file, or calculated from maximal and minimal spectral radiance values (Lu et al. 2002).

13.5.2 MAPPING ISA WITH QUICKBIRD IMAGERY

QuickBird imagery is used to develop ISA data that is used as a reference for establishing a calibration model for refining the Landsat-derived ISA image. QuickBird imagery has four multispectral bands with 2.4-m spatial resolution and one panchromatic band with 0.6-m spatial resolution. In order to make full use of both the multispectral and panchromatic images, the wavelet merging technique (Lu et al. 2008) was used to merge the QuickBird multispectral bands and panchromatic band into a new multispectral image with 0.6-m spatial resolution. A hybrid method that consisted of thresholding, unsupervised classification, and manual editing was used to produce the ISA image from the fused QuickBird imagery (Lu et al. 2011) (see Figure 13.4). The fact that vegetation has significantly different spectral features comparing with ISA in the NDVI image and clear and deep water bodies have much lower spectral values than ISA in the NIR wavelength image, the vegetation and
Mapping Impervious Surface Distribution

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 near-infrared images and then masking vegetation out with the selected threshold on the NDVI image, and masking water out with the selected thresholds on the NIR image, (2) extracting spectral signatures of the nonvegetation pixels, using an unsupervised classification algorithm to classify the extracted spectral signatures into 50 clusters and merging the clusters into ISA and other classes, and (3) manually editing the extracted ISA image (Lu et al. 2011). Although unsupervised classification can separate most ISA from bare soils and wetlands, some confusion still remains between bare soil and bright ISA, and among dark ISA, shadowed ISA, wetlands, or shadows from tree crowns. Therefore, visually interpreting the extracted ISA image is necessary to further refine the ISA image quality by eliminating the confused pixels (e.g., bare soils, non-ISA shadows, and wetlands).

Accuracy assessment is conducted with the error matrix approach (Congalton and Mead 1983; Congalton 1991; Janssen and van der Wel 1994; Foody 2002; Congalton and Green 2008). A total of 450 test samples were selected with the random sampling method. The analyst then examined each test sample plot to decide whether it was correctly classified as ISA or not based on visual interpretation on the QuickBird color composite. When the accuracy is satisfied, the ISA image with spatial resolution of 0.6 m is finally aggregated to 30 m to generate fractional ISA image for use as reference data.

**13.5.3 Developing Per-Pixel Based ISA from Landsat Images**

Per-pixel ISA mapping is often based on the image classification of spectral signatures (Shaban and Dikshit 2001; Lu et al. 2011), but per-pixel based classification methods based on medium or coarse spatial resolution images cannot effectively extract the ISA because of the spectral confusion between ISA and other land covers and the mixed pixel problems, especially in a complex urban–rural frontier (Wu and Murray 2003; Lu and Weng 2006a). This research for mapping per-pixel ISA was based on...
the combination of filtering images and unsupervised classification of Landsat spectral signatures. The fact that the red-band image in Landsat TM has high spectral values for ISA but has low spectral values for vegetations and water/wetlands provides a potential way to rapidly map ISA. The minimum and maximum filter with a window size of 3 × 3 pixels was separately applied to the Landsat red-band image. The image differencing between maximum and minimum filtering images was used to highlight linear features (mainly roads) and other ISAs. Examination of the difference image indicated that a threshold of 13 value can extract the ISA image. The spectral signature of the initial ISA image was then extracted and was further classified into 60 clusters using an unsupervised classification method to refine the ISA image by removing the non-ISA pixels. Finally, manual editing of the ISA image was conducted to make sure that all ISAs, especially in urban regions, were extracted. The final per-pixel based ISA image was overlain on the TM color composite to visually examine the ISA mapping quality in order to make sure all urban area and major roads were properly extracted.

13.5.4 MAPPING FRACTIONAL ISA DISTRIBUTION

As per-pixel methods based on medium or coarse spatial resolution often overestimate or underestimate ISA, it is important to estimate fractional ISA images in order to improve area estimation. Of the many methods for mapping ISA (Slonecker et al. 2001; Brabec et al. 2002), the LSMA-based method has proven valuable for extracting fractional ISA from Landsat images (Wu and Murray 2003; Lu and Weng 2006a,b). LSMA is regarded as a physically based image-processing tool. It supports repeatable and accurate extraction of quantitative subpixel information (Smith et al. 1990). The LSMA approach assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components (endmembers) within the pixel and that the spectral proportions of the endmembers represent proportions of the area covered by distinct features on the ground (Adams et al. 1995; Mustard and Sunshine 1999). The mathematical model can be expressed as

$$R_i = \sum_{k=1}^{n} f_k R_{ik} + \varepsilon_i$$  \hspace{1cm} (13.3)

where $i$ is the number of spectral bands used; $k = 1, ..., n$ (number of endmembers), $R_i$ is the spectral reflectance of band $i$ of a pixel that contains one or more endmembers, $f_k$ is the proportion of endmember $k$ within the pixel, $R_{ik}$ is known as the spectral reflectance of endmember $k$ within the pixel on band $i$, and $\varepsilon_i$ is the error for band $i$. For a constrained least squares solution, $f_k$ is subject to the following restrictions:

$$\sum_{k=1}^{n} f_k = 1 \text{ and } 0 \leq f_k \leq 1$$  \hspace{1cm} (13.4)
Mapping Impervious Surface Distribution

\[
\text{RMSE} = \sqrt{\sum_{i=1}^{m} \frac{e_i^2}{m}} \quad \text{(13.5)}
\]

The root-mean-square error (RMSE) is used to assess the fit of the model. It is calculated for all image pixels. The larger the RMSE is, the worse the fit of the model is. So the error image can be used to assess whether the endmembers are properly selected and whether the number of selected endmembers is sufficient.

In the LSMA approach, endmember selection is a key step, and many approaches have been developed (Lu et al. 2003; Theseira et al. 2003). In practice, image-based endmember selection methods are frequently used because image endmembers can be easily obtained and they represent the spectra measured at the same scale as the image data. Image endmembers can be derived from the extremes of the image feature space, assuming that they represent the purest pixels in the images (Mustard and Sunshine 1999). In order to effectively identify image endmembers and to achieve high-quality endmembers, different image transform approaches such as principal component analysis (PCA) and minimum noise fraction (MNF) may be used to transform the multispectral images into a new data set (Green et al. 1988; Boardman and Kruse 1994). Endmembers are then selected from the feature spaces of the transformed images (Garcia-Haro et al. 1996; Cochrane and Souza 1998; van der Meer and de Jong 2000; Small 2001, 2002, 2004). In this research, four endmembers (i.e., high-albedo objects, low-albedo objects, vegetation, and soil) were selected from the feature spaces formed by the MNF components. A constrained least squares solution was then used to unmix the Landsat TM multispectral image into four fractional images and one error image.

Previous research indicates that the high-albedo fraction image contains the bright ISA objects such as building roofs with high spectral values, and low-albedo fraction image contains the dark ISA objects such as dark roads and streets with low spectral values (Lu and Weng 2006a,b). Therefore, the overall ISA image can be extracted from the addition of high-albedo and low-albedo fraction images. One critical step in mapping ISA is to remove the non-ISA pixels. The strategy of mapping fractional ISA can be illustrated based on the LSMA-based methods and per-pixel based method (Figure 13.5). By combining per-pixel ISA and high- and low-albedo fraction images, a fractional ISA image was then generated with the following rules: if the pixel is ISA in the per-pixel based ISA image, the pixel value is then extracted from the sum of high-albedo and low-albedo fraction images; otherwise, assign zero to the pixel.

13.5.5 Refining ISA by Integrated Use of Landsat- and QuickBird-derived ISA Images

Previous research also indicates that the developed ISA data set from Landsat TM images is often overestimated or underestimated, depending on the proportion of ISA in a pixel (Wu and Murray 2003; Lu and Weng 2006a). In the complex urban–rural landscape, ISA estimation with LSMA-based method often overestimates its area.
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It is necessary to calibrate this bias. One method is to develop a regression model to calibrate the TM-derived ISA images. In this research, the overlap area between the 2008 QuickBird and the corresponding Landsat-derived ISA images was used for sample collection based on this rule: select one pixel for every five intervals on the overlapped images. Because many pixels were non-ISA, they had zero values. After removal of all samples with zero values, 1512 samples were used to develop the calibration model. A scatterplot of these samples was used to examine the relationship between the Landsat-derived and QuickBird-derived ISA images. A regression model was developed to conduct the calibration.

13.6 RESULTS AND DISCUSSION

13.6.1 ISA MAPPING WITH QUICKBIRD IMAGERY

A high-quality ISA data set from QuickBird imagery is required because it is used as reference data for calibrating Landsat-derived ISA data set. The accuracy assessment based on randomly selected 450 sample plots indicated that 98% overall accuracy was achieved, according to visual interpretation on the QuickBird color composite. The spatial patterns of ISA distribution can be shown in Figure 13.6. The QuickBird-derived ISA data were then aggregated from 0.6 to 30 m cell sizes to generate fractional ISA data for use in linking it to Landsat TM image for calibration.

13.6.2 EVALUATION OF PER-Pixel ISA IMAGE FROM LANDSAT TM IMAGERY

Evaluation of the per-pixel ISA image based on overlaying it on the TM color composite indicates that a combination of filtering images and unsupervised classification method developed in this research can effectively extract the pixel-based ISA data set in the complex urban–rural frontier. In per-pixel based results, each

FIGURE 13.5 Strategy of developing fractional impervious surface images based on the combination of linear spectral mixture analysis and per-pixel based method.
extracted ISA pixel is assumed to be 100% ISA. This data set is useful for visually interpreting the ISA distribution, but not suitable for area statistics. Therefore, it is necessary to produce a subpixel ISA data set for area statistical purpose in order to remove the impact of the mixed pixel problem.

13.6.3 Development of Fractional ISA Image from Landsat TM Imagery

The four fraction images developed from Landsat TM imagery with the LSMA approach have physical meanings as described in Section 13.2. ISA is mainly concentrated on high-albedo and low-albedo fraction images; thus, the fractional ISA data can be directly extracted through the addition of the high-albedo and low-albedo fraction images. However, some roads appear in the soil fraction image due to the confusion of their spectral signatures (see Figure 13.7), and some non-ISA pixels, such as water, are also included in the initial fractional ISA image. Therefore, the per-pixel based ISA image is used to mask out the non-ISA pixels from the fractional ISA image. A comparison of per-pixel ISA can be summarized (Figure 13.8a and b). Fractional ISA (Figure 13.8c and d) images indicated that the area amount may be significantly overestimated by the per-pixel ISA image. Because of the limitation of the LSMA method in extracting ISA information from other land covers, underestimation or overestimation of ISA is common, as shown in previous research (Lu and
13.6.4 **Calibration of the Landsat-Derived Fractional ISA with the QuickBird-Derived ISA Image**

In theory, if the ISA data are accurately estimated from both Landsat TM and QuickBird images, the scatterplot between both fractional ISA data sets should show a very good linear relationship. As shown in Figure 13.9, the ISA image developed in this research demonstrates a reasonably good result, although overestimation occurred when the ISA accounted for a relatively small proportion in a pixel and underestimation occurred when the ISA accounted for a large proportion in a pixel. This trend is similar in other previous research (Wu and Murray 2003; Lu and Weng 2006; Greenfield et al. 2009). Overall, a good linear relationship exists between the fractional ISA images developed independently from 2008 Landsat TM
Based on the samples from QuickBird- and Landsat-derived ISA images, a linear regression model is established as follows:

\[ y = 1.0674x - 0.0119; \quad R^2 = 0.45 \quad (13.6) \]

where \( x \) is the fractional ISA values from 2008 Landsat TM image, and \( y \) is the calibrated fraction ISA values. For the non-ISA pixels (i.e., \( x \) equals zero), assign a zero value to that pixel; otherwise, this equation was used to calibrate the entire image of 2008 Landsat TM-derived fractional ISA image. When the ISA was calculated from the per-pixel ISA image, the ISA for Lucas município (see Figure 13.2) was 99.87 \( \text{km}^2 \), accounting for 1.291% of the study area. However, when the ISA was calculated from the calibrated fractional ISA data set, the ISA became only 56.86 \( \text{km}^2 \),

**FIGURE 13.8** Comparison of impervious surface results with pixel-based (a and b) and subpixel-based (c and d) methods.
accounting for only 0.735%. This implies that development of fractional ISA data set is required for ISA measurement, especially in an urban–rural frontier.

13.7 CONCLUSIONS

The complexity of ISA in the urban landscape and the mixed pixel problem in medium and coarse spatial resolution images make the mapping of ISA a challenging task. Traditional per-pixel based image classification methods cannot effectively handle the mixed pixel problem, and subpixel-based methods cannot effectively separate the pixels of ISA from other land covers; thus, underestimation or overestimation of the ISA are common, depending on the proportion of ISA in a pixel. The method described in this chapter, which is based on the combination of per-pixel based ISA mapping with filtering and unsupervised classification, and subpixel-based method with the LSMA approach, can effectively map ISA distribution with Landsat images. The calibration with QuickBird-derived ISA data set can further reduce the bias caused by mixed pixel problems and thus improve ISA mapping performance. The major advantage of the method described in this chapter is that the ISA estimation can be considerably improved comparing with per-pixel based results in a complex urban–rural frontier. More research is needed to apply this method to other study areas and other dates of Landsat images to examine its transferability and robustness.

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REFERENCES


No. 10-03

No. 10-04

No. 10-05

No. 10-06

No. 10-09

No. 10-10

No. 10-11

No. 10-12

No. 10-13

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