Quantifying high-resolution impervious surfaces using spectral mixture analysis

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Impervious surface distribution and its temporal changes are considered key urbanization indicators and are utilized for analysing urban growth and influences of urbanization on natural environments. Recently, urban impervious surface information was extracted from medium/coarse resolution remote sensing imagery (e.g. Landsat ETM+ and AVHRR) through spectral analytical methods (e.g. spectral mixture analysis (SMA), regression tree, etc.). Few studies, however, have attempted to generate impervious surface information from high resolution remotely sensed imagery (e.g. IKONOS and Quickbird). High resolution images provide detailed information about urban features and are, therefore, more valuable for urban analysis. The improved spatial resolution, however, also brings new challenges when existing spectral analytical methods are applied. In particular, a higher spatial resolution leads to reduced boundary effects and increased within-class variability. Taking Grafton, Wisconsin, USA as a study site, this paper analyses the spectral characteristics of IKONOS imagery and explores the applicability of SMA for impervious surface estimation. Results suggest that with improved spatial resolution, IKONOS imagery contains 40–50% of mixed urban pixels for the study area, and the within-class variability is a severe problem for spectral analysis. To address this problem, this paper proposes two approaches, interior end-member set selection and spectral normalization, for SMA. Analysis of results indicates that these approaches can reasonably reduce the problems associated with boundary effects and within-class variability, therefore generating better impervious surface estimates.

1. Introduction

Urban areas in the USA have expanded at unprecedented rates in the past decades due to urban population growth and sprawl. According to the US Department of Agriculture (2000), approximately 10 million hectares of rural lands have been developed from 1982 to 1997. In particular, 4.1 million hectares of forest lands, 2.8 million hectares of croplands, 1.7 million hectares of pasturelands and 1.3 million hectares of rangelands have been converted to urban land uses. Urban population growth is considered a major force for urban expansion. From 1900 to 2000, the total population of urban areas in the USA has increased from around 30 million to 226 million, accounting for a percentage increase of 39.6% to 79.2%. Besides population growth, sprawl may be another reason for urban expansion, as over 90% of recent urban developments have occurred in suburban and exurban areas and lifestyles in these low density urban areas are considered appealing to many US citizens (Nelson 1992, Duany and Plater-Zyberk 2000).

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While urban growth brings economic benefits, it also leads to environmental degradation and negative social effects. Urban impervious surfaces accelerate storm water runoff, and cause non-point water pollution. In addition, the increasing automobile traffic due to rapid urban expansion has severely degraded air quality. According to the US Environmental Protection Agency (2000), approximately 80% of carbon monoxides, 53% of nitrogen oxides and 43% of volatile organic compounds can be attributed to urban transportation. Congestion is also an outcome of urban expansion, with increased time spent in commuting and a lesser degree of accessibility (Newman and Kenworthy 1999). It is estimated that the costs associated with congestion are over $US40 billion a year (Transportation Research Board 1994). Therefore, understanding and monitoring the process of urban expansion is an important research topic for urban planners and scientists.

A variety of data sets have been generated to represent urban extent and understand urbanization process. Traditionally, census data have been relied upon primarily in analysing urban systems. In particular, urban, suburban and rural areas are defined according to census population density. However, census data are often too coarse and out of date for supporting the needs of urban analysis (Plane and Rogerson 1994, Harris and Longley 2000). Besides census data, urban land-use/land cover (LULC) data have been widely utilized in quantifying urban areas and monitoring urban change. Land-use/land cover data, however, do not contain detailed information about built-up areas (Ji and Jensen 1999, Rashed et al. 2005). Moreover, the definition of land-use types is a somewhat subjective process, which may not represent actual urban development.

In contrast with census and LULC data, impervious surfaces, which are the major components of urbanized regions, have been found to reveal significant information about built-up areas, and can be utilized to quantify urban development and land-use intensity. To prove the importance of impervious surfaces in urban analysis, Ridd (1995) proposed the vegetation–impervious surface–soil (V–I–S) model to parametrize biophysical composition of urban environments. In this model, urban environments are described as a combination of green vegetation, impervious surface and soil, if water surfaces are ignored. Applying this model, Rashed et al. (2001) and Lu and Weng (2004) proved that the spatial extent of urban and suburban development can be quantified accurately through the information of impervious surface, vegetation and soil. Moreover, impervious surface distribution and its changes were identified as an important urbanization indicator, and utilized for analysing urban growth rates and spatial patterns (Yang et al. 2003b, Rashed et al. 2005, Xian and Crane 2005, Yang and Liu 2005). In addition to quantifying urban development and monitoring urban growth, the distribution of impervious surfaces was utilized to assess the influence of urban development on urban climate, water quality and natural habitat. As an example, Weng et al. (2004) found that a significant relationship exists between impervious surface and urban heat island effect. Moreover, the US Environmental Protection Agency (2003) has identified the percentage of impervious surface within a watershed as an important indicator for water and terrestrial ecosystem health. Because of the important roles that impervious surfaces play, the generation of impervious surface data has become crucial in urban analysis.

A traditional method for generating impervious surface information is through manually digitizing aerial photographs. Although relatively accurate, the digitizing process is labour intensive and time consuming. Automatic methods, such as
spectral mixture analysis (SMA), regression tree (RT) model, artificial neural network (ANN) and regression analysis, have been developed and applied in a number of urban areas with some success (Flanagan and Civco 2001, Small 2003, 2005, Wu and Murray 2003, Wu 2004, Yang et al. 2003a, b, Yang and Liu 2005). These methods, however, were applied primarily to medium/coarse resolution remote sensing imagery, such as Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data (30 m × 30 m) and Advanced Very High Resolution Radiometer (AVHRR) data (1.1 km × 1.1 km). The resulting impervious surface estimates, therefore, cannot attract the interests of urban planners because of the coarse spatial resolution.

The recently launched IKONOS sensor, with high spatial resolutions (4 m multispectral and 1 m panchromatic) and multiple spectral bands, offers an ideal opportunity for producing high resolution impervious surface information (Sawaya et al. 2003, Small 2003). This, however, also brings new challenges when existing automatic methods are applied for urban applications. With an increased spatial resolution, the proportion of pure pixels to the total pixels is likely to be higher when compared to medium resolution imagery (e.g. Landsat TM and Satellite Pour l’Observation de la Terre (SPOT)) (Hsieh et al. 2001), and the number of mixed pixels can be largely reduced. As a result, methods for sub-pixel analysis, such as SMA, may not be appropriate for such applications, and the traditional per-pixel classification may be a better alternative. The other challenge involves the increased within-class variability due to improved spatial resolution. It has been observed that, with the improvement of spatial resolution, within-class spectral variance increases, and spectral separability among classes diminishes (Latty et al. 1985, Hsieh et al. 2001).

The objective of this paper is to explore whether a popular impervious surface estimation technique, spectral mixture analysis, can be applied to high resolution remote sensing imagery. This paper begins with examining spectral characteristics of IKONOS imagery acquired for the Village and Town of Grafton, Wisconsin, USA. In particular, the problems of reduced boundary effects (mixed pixels) and increased within-class variation will be examined. With the knowledge of spectral characteristics of IKONOS imagery, this paper evaluates whether SMA with interior end-member set selection and spectral normalization can address these problems for high resolution impervious surface estimation. The rest of this paper is organized as follows: section 2 describes the study area and remotely sensed data, including IKONOS imagery and aerial photographs; section 3 analyses the spectral characteristics of the IKONOS imagery regarding the aspects of boundary effects and within-class variation, and highlights the issues of improved spatial resolution for SMA; section 4 develops two approaches – interior end-member set selection and spectral normalization – to reduce the problems associated with high-resolution imagery. A comparative analysis of four SMA methods is reported in section 5. Accuracy assessment of these methods is detailed in section 6 and, finally, conclusions and discussion are given in section 7.

2. Study area and data

Grafton (including the village and town) in Ozaukee County, Wisconsin, USA (figure 1) was selected as the study area. Being about 30 km north of Milwaukee City, Wisconsin, Grafton occupies a geographical area of 65.4 km², with more than 14 000 residents and approximately 5700 housing units according to Census 2000.
Land uses in this region include commercial (town of Grafton), residential, transportation, agricultural, forestry, as well as other rural lands. Grafton encountered rapid growth from 1970 to 2000. In fact, the population of Grafton increased approximately 58% during these 30 years and the number of housing units reached about 5800 in 2000, more than twice the number in 1970. Moreover, this growth trend is likely to continue in future decades (SWRPC 2004). For the study area, an IKONOS image (figure 1(b)), acquired on 3 September 2002, was obtained. The image was preprocessed and the reflectance for each pixel was calculated from

Figure 1. Village and Town of Grafton, Ozaukee, Wisconsin. (a) Geographical location of Grafton in Wisconsin (UTM, zone 16, datum WGS 84). (b) IKONOS imagery for Grafton obtained on 3 September 2002 (4, 2, 1 band combination, 4 m spatial resolution); colour cyan indicates impervious surfaces, dark cyan indicates soil, and red indicates vegetation. (c) Colour aerial photograph taken in November 2002 (true colour image with 0.61 m spatial resolution).
its digital number (DN) values under the guide of Space Imaging online documents (IKONOS 2005). In order to evaluate the results of impervious surface estimation, a colour digital aerial photograph (figure 1(c)) for Grafton was also obtained from the American Geographical Society Library (AGSL) in the University of Wisconsin-Milwaukee, USA. This photograph was acquired in November 2002, with a spatial resolution of about 2 feet (0.61 m). Both the IKONOS image and aerial photograph were re-projected to the Universal Transverse Mercator (UTM) projection (zone 16, datum WGS84). Moreover, a further georeference was conducted to reduce geometry misregistration between the IKONOS image and the aerial photograph. In addition to remote sensing data, land-use data from 2000 for the study area were acquired from Southeast Wisconsin Regional Planning Commission (SWRPC 2004).

3. Spectral characteristics of IKONOS imagery

3.1 Mixed or pure pixels?

IKONOS multiple spectral images (MSI) have a spatial resolution of 4 m, which is smaller than the size of many urban features (Small 2003). Therefore, unlike medium-resolution remote sensing imagery, for IKONOS imagery, pure pixels may dominate a study area. Thus, SMA, which assumes that each pixel contains several land cover types, may not be appropriate for high resolution remote sensing imagery. This study attempted to quantify the amount of mixed and pure pixels in an IKONOS image, and explore the necessity of applying sub-pixel analytical methods.

3.1.1 Classification of colour aerial photograph. A hard classification was conducted on the colour aerial photograph with two classes: urban impervious surfaces and rural land cover types (e.g. soil, agricultural lands, water, etc.). The classification was performed in three steps: (1) stratification of urban and rural land uses; (2) unsupervised and supervised classification; and (3) post-classification and manual editing. The first step divides the data in the aerial photo into two classes: urban and rural, based on the SWRPC 2000 land use data set. For both urban and rural land uses, unsupervised and supervised classification was conducted following the guided clustering methods of Reese et al. (2002). Post-classification and manual editing were applied to these resulting images to ensure classification accuracy.

3.1.2 Evaluation of the proportion of mixed pixels in 4 m IKONOS imagery. In order to compare with IKONOS imagery, the classification results from the colour aerial photograph were resampled to 4 m resolution (same pixel size with the IKONOS MSI) such that the value of each pixel represents the fraction of urban impervious surfaces within that pixel. Therefore, a pixel with a value of 1 in the resampled aerial photograph indicates pure impervious surfaces; 0 indicates pure non-impervious surfaces; and 0.5 indicates 50% of impervious surfaces within that pixel. Then a pixel-to-pixel comparison was conducted to evaluate the proportion of mixed pixels in the IKONOS imagery. Results (table 1) indicate that for the Village of Grafton (with 9.3% impervious surfaces) and Town of Grafton (29.6% impervious surfaces), the proportion of pure impervious surface pixels out of the total number of pixels containing impervious surfaces is 52.0% and 56.8%, respectively. These results indicate that there are about 40–50% of mixed pixels; therefore, sub-pixel analysis may still be a valid option for impervious surface
estimation. However, such analysis must also take the pure pixels into consideration.

3.2 Within-class variations

It was observed that, with improved spatial resolution, a remote sensing image is likely to have a higher within-class variation compared to a medium-resolution remote sensing image (Hsieh et al. 2001). In this research, the within-class spectral variation for urban impervious surfaces of the IKONOS imagery is explored using two methods: (1) coefficient of variation measurement and (2) spectral scatter plot after minimum noise fraction (MNF) transformation.

3.2.1 Coefficient of variation measurement. The coefficient of variation ($V$) is a dispersion measurement for a probability distribution. It is a dimensionless number, which permits the comparison of internal variation for populations with significant different mean values. In this research, the coefficient of internal variation for pure urban impervious surface class in IKONOS band $i$ is calculated as follows:

$$V_i = \frac{\sigma_i}{\mu_i} \times 100\%$$

where $\sigma_i$ is the standard deviation and $\mu_i$ is the mean of the spectral reflectance for pure urban impervious surface class in band $i$. Results (table 2) indicate that for the IKONOS reflectance image, the coefficients of variation for each band for pure impervious surface pixels range from 27% (band 2 and 3) to 58% (band 4).

3.2.2 Spectral scatter plot after minimum noise fraction (MNF) transformation. In order to assess further the within-class spectral variation of the IKONOS image, spectral scatter plots of the MNF components of the IKONOS reflectance image were used. Unlike principal component (PC) transformation, which places components according to their variances, MNF transformation orders components according to their signal to noise ratios. Therefore, the MNF transformation is

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength (um)</th>
<th>Reflectance image</th>
<th>Normalized image</th>
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<tr>
<td></td>
<td>Mean</td>
<td>Standard deviation</td>
<td>Coefficient of variation (%)</td>
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<tr>
<td>Band 1</td>
<td>0.445–0.516</td>
<td>46.25</td>
<td>14.04</td>
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<tr>
<td>Band 2</td>
<td>0.506–0.595</td>
<td>42.72</td>
<td>11.53</td>
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<tr>
<td>Band 3</td>
<td>0.632–0.698</td>
<td>52.57</td>
<td>14.19</td>
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<tr>
<td>Band 4</td>
<td>0.757–0.853</td>
<td>28.64</td>
<td>16.68</td>
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considered superior in keeping information (not the variances) in its first several components. In this paper, MNF transformation was implemented using the minimum/maximum autocorrelation factors (MAF) procedure proposed by Green et al. (1988). The degree of within-class spectral variation can be explored through analysing the resulting feature space representation of the first three MNF components (figure 2); when compared with the original IKONOS images, a high spectral variation can be found within the urban impervious surface class. As illustrated in figure 2(a), it is clear that pure urban impervious surfaces demonstrate highly different spectral characteristics. This high spectral variation of pure impervious surfaces can also be identified in figures 2(b) and (c). Therefore, unlike

![Figure 2. Feature space scatter plot of the first three maximum noise fraction (MNF) components for the IKONOS reflectance image (MNF1, 2 and 3 accounts for 72.4%, 26.5% and 0.9% of the total signal to noise ratio, respectively. (a) Dark impervious surface includes asphalt (roads, parking lots and low reflectance roofs) and bright impervious surface includes concrete, glass, etc. (b) Dashed line indicates the exterior end-member set and solid line indicates the interior end-member set.](image-url)
medium resolution remote sensing images (e.g. Small 2005), it is a much more challenging task to choose a single end-member from IKONOS imagery to represent a variety of urban impervious surfaces.

4. End-member selection and spectral normalization

Analysis of the spectral characteristics of the IKONOS imagery, in particular the issues of mixed pixels and within-class variations, showed that SMA may still be a valid approach. The selection of end-members, however, is becoming a difficult task due to the high percentage of pure pixels and large within-class spectral variations of urban impervious surfaces. To address these problems, this paper proposes two approaches: (1) interior end-member selection; and (2) spectral normalization.

4.1 End-member selection: interior or exterior set

For medium resolution remote sensing imagery, exterior end-members, which are identified at external vertices of pure land cover types in a spectral feature space after either MNF or PC transformation, are often utilized. The exterior end-members are statistically valid and generate the lowest RMS error (RMSE). For high resolution remote sensing imagery, however, the selection of exterior end-members may produce significant errors for pure land covers (e.g. impervious surfaces), which are spectrally highly different from the chosen end-members. Interior end-members, which are chosen from the internal vertices of pure land cover types, may produce better results. Carpenter et al. (1999) and Lee and Lathrop (2005) suggested that a set of interior end-members performs better than exterior end-members for vegetation and urban sub-pixels analysis when applied to medium resolution remote sensing imagery. With a set of interior end-members (figure 2(b)), pixels located within the inner space enclosed by the interior end-members are linearly unmixed, and the pixels located outside the inner space are proportionally unmixed to the two (or one) closest end-members. Statistically, the interior end-member set may introduce a higher RMSE, especially for the pixels located outside the inner space. This method, however, may partially address the spectral variations of pure pixels and produce better estimates.

4.2 Spectral normalization

Spectral normalization was proposed by Wu (2004) to reduce spectral variations associated with absolute brightness, while maintaining spectral shape information to separate major land cover types. This method has proven effective in urban applications (Wu 2004, Yuan and Bauer 2007) and was also utilized by Zhang et al. (2005) for unmixing lichens and rocks. The formula for spectral normalization is:

\[ \bar{R}_b = \frac{R_b}{m} \times 100 \]  

where \( m = \frac{1}{n} \sum_{b=1}^{n} R_b \), \( \bar{R}_b \) is the normalized reflectance and \( R_b \) is the original reflectance for band \( b \) at each pixel; \( m \) is the average reflectance for that pixel; and \( n \) is the total number of bands (4 for IKONOS imagery). An MNF transformation was performed on the normalized image (figure 3) and the scatter plots of the first three MNF components are illustrated in figure 4. The coefficients of variation (table 2) of these normalized images are significantly lower than those of the original
images. In particular, when compared to the reflectance IKONOS image, the coefficients of spectral variation for pure impervious surfaces in the normalized image are reduced by 17–20% for bands 1, 2 and 3, and 11% for band 4. The reduced spatial variation of pure impervious surfaces can also been identified in figure 4. In particular, pure impervious surfaces are more likely to form dense clusters (figure 4(c)), instead of spreading over the plotting area (figure 2).

5. Spectral mixture analysis

With the pre-processed IKONOS imagery and a selected end-member set, it is necessary to estimate impervious surface information through applying the SMA method. Spectral mixture analysis assumes that a pixel in a remote sensing image contains a number of land covers and the spectrum of the pixel is a combination of spectra of these pure land cover types, called end-members. The fraction of each pure land cover type can be calculated by modelling the relation between the mixed spectrum and the spectrum of each pure land cover type. Dependent on the significance of multiple scattering of light on land cover types, SMA can be divided into linear and nonlinear models. Linear models have been used popularly in urban applications and, therefore, utilized in this paper (Phinn et al. 2002, Wu and Murray 2002).
2003, Wu 2004). SMA was applied successfully to medium-resolution remote sensing imagery (e.g. Landsat TM and ETM+), but few studies applied the SMA method to IKONOS imagery, which has a much higher spatial resolution and fewer spectral bands (e.g. 4 bands compared to 6 bands in Landsat imagery). One exception is the work of Small (2003), who applied SMA to explore the mixing space of urban reflectance using IKONOS MSI imagery, but he did not explicitly estimate imperviousness. In this study, two sets of end-members, interior and exterior end-members, were selected by analysing the feature space representation and visualizing the IKONOS imagery and the photographs. The interior end-member sets were chosen as the internal vertices of pure land cover types, while the exterior end-member sets were identified as the external vertices of the scatter plots (figures 2 and 4). The end-member spectra of interior and exterior end-member sets for the reflectance and normalized IKONOS imagery are illustrated in figure 5. As a result, four SMA models (table 3) were constructed for impervious surface estimation based on whether the interior end-member set selection and spectral normalization are applied.

With a selected end-member set and IKONOS imagery (reflectance or normalized), SMA models were conducted for calculating the fractions of vegetation, impervious surface and soil for each pixel. These SMA models were formulated as follows:

\[ R_b = \sum_{i=1}^{n} f_i R_{i,b} + e_b \]  

Figure 4. Feature space representation of the first three maximum noise fraction (MNF) components for the normalized reflectance IKONOS image (MNF1, 2 and 3 accounts for 89.7%, 6.3% and 2.3% of the total signal to noise ratio, respectively). (c) Dashed line indicates the exterior end-member set and solid line indicates the interior end-member set.
Where \( \sum_{i=1}^{n'} f_i = 1 \) and \( f_i \geq 0 \), \( R_b \) is the reflectance (or normalized reflectance) for a pixel; \( R_{i,b} \) is the reflectance (or normalized reflectance) at band \( b \) for end-member \( i \); \( f_i \) is the fraction of end-member \( i \); \( n' \) is the number of end-members; and \( e_b \) is the residual. These models were solved using a least squares method in which the residual \( e_b \) is minimized. The outputs of these SMA models are the fraction images for vegetation, impervious surface and soil. The fraction images of impervious surfaces resulting from these four SMA models are illustrated in figure 6. By visual inspection of these images, it has been found that with the exterior end-member sets (figures 6(a) and (c)), the impervious surface fractions are likely to be underestimated. In particular, within the Town of Grafton, impervious surface fractions for commercial areas are underestimated by approximately 20–30\%. Associated with the underestimation, confusion between impervious surfaces and bare soil is also obvious. In fact, figures 6(a) and (c) illustrate that some bare soils in the Village of

<table>
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<tr>
<th>Table 3. Comparisons of spectral mixture analysis models.</th>
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<tbody>
<tr>
<td>Interior end-member set selection</td>
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<tr>
<td>----------------------------------</td>
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<tr>
<td>Model 1</td>
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<td>Model 2</td>
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<td>Model 3</td>
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<td>Model 4</td>
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Grafton are considered erroneously as impervious surfaces. With the interior end-member sets (figures 6(b) and (d)), however, the underestimation of impervious surfaces in the Town of Grafton is partially addressed; and with the normalized IKONOS image (figure 6(d)), the confusion between impervious surfaces and bare soil is also likely to be reduced.

6. Accuracy assessment

Besides visual comparisons of impervious surface fraction images, an accuracy assessment was carried out to compare quantitatively the performances of these four models.
models with the classified aerial photograph as the reference image. Two parameters, systematic error (SE; equation (4)) and mean average error (MAE; equation (5)) were used to quantify the accuracy of impervious surface estimation.

\[
SE = \frac{1}{N} \sum_{i=1}^{N} \left( \hat{I}_i - I_i \right) / \sum_{i=1}^{N} I_i
\]

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |I_i - \hat{I}_i|
\]  

Where \( \hat{I}_i \) is the estimated impervious surface fraction for pixel \( i \); \( I_i \) is the ‘true’ impervious surface fraction obtained from the classified aerial photograph; and \( N \) is the total number of pixels. SE measures the overall estimation accuracy for the entire study area; and MAE quantifies the relative estimation error at the IKONOS pixel level. For the calculation of MAE, a multiple resolution procedure proposed by Pontius (2000, 2002) was also used. In particular, in addition to the pixel-wise comparison, five different aggregation scales, \( 3 \times 3, 5 \times 5, 7 \times 7, 10 \times 10 \) and \( 20 \times 20 \) pixels, were utilized for the MAE calculation. As pointed out by Pontius (2000, 2002) and Pontius and Cheuk (2006), for a particular scale, the estimation error is composed of two types of errors: location error and quantity error. For the accuracy assessment at the entire study area level, the location error is zero and only quantity error exists. At the pixel level, however, the location error is the most significant and it may be reduced when the size of the measurement unit increases (e.g. from pixel-wise to \( 3 \times 3 \)-pixel comparison).

Table 4 reports the systematic errors (SEs) of impervious surface estimation for the entire study area, Town of Grafton, and Village of Grafton using the four SMA methods. For the entire study area, low SEs were achieved for the SMA with exterior end-member set and reflectance image (2.26%), and with interior end-member set and normalized image (2.66%). For the Town of Grafton, the SMA models with exterior end-member set underestimated impervious surface areas (−10.48% and −2.42% for reflectance and normalized imagery); while the models with interior end-member sets slightly overestimated impervious surface areas (6.45% and 5.65% for reflectance and normalized imagery). For the Village of Grafton, all SMA methods overestimated impervious surface areas, but the model with interior end-member set and normalized image has the slightest overestimation (2.07%).

The comparative analysis of SE gives only an overall performance of each SMA method. For a detailed analysis, the multiple-resolution MAE calculation was carried out and the results are shown in figure 7. Several impressions can be taken away from these results. First, with the increment of measurement size (from pixel-wise to \( 3 \times 3 \)-pixel, \( 5 \times 5 \)-pixel, etc.), the MAE decreases accordingly. For example, for the SMA with interior end-member set and spectral normalization, the MAE is 9.2% for the

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<th>Entire study area (%)</th>
<th>Town of Grafton (%)</th>
<th>Village of Grafton (%)</th>
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<tbody>
<tr>
<td>Exterior end-member set</td>
<td>2.26</td>
<td>−10.48</td>
<td>4.79</td>
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<tr>
<td>Reflectance image</td>
<td></td>
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<tr>
<td>Interior end-member set</td>
<td>7.72</td>
<td>6.45</td>
<td>7.98</td>
</tr>
<tr>
<td>Reflectance image</td>
<td></td>
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</tr>
<tr>
<td>Exterior end-member set</td>
<td>5.06</td>
<td>−2.42</td>
<td>6.54</td>
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<tr>
<td>Normalized image</td>
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<tr>
<td>Interior end-member set</td>
<td>2.66</td>
<td>5.65</td>
<td>2.07</td>
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<td>Normalized image</td>
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pixel-to-pixel comparison, and drops to 4.8% for the 20 × 20-pixel comparison and continues to drop until it reaches the SE value (2.66%). Secondly, for the Town of Grafton, the performances of these four models are similar; and the model with interior end-member set and spectral normalization slightly outperforms the other three methods. Figure 7(b) also indicates, for the Town of Grafton, that the MAE drops more rapidly with the increment of measurement size. For example, for the SMA with interior end-member set and spectral normalization, the MAE drops from 20% for the per-pixel comparison to 12% for the 5 × 5-pixel comparison. Finally, in the Village of Grafton, the SMA with interior end-member set and spectral normalization performs significantly better than other methods (figure 7(c)), and the MAE is approximately 5% lower than the value obtained with other methods. This indicates that a combination of interior end-member set and spectral normalization can effectively address the confusion between impervious surfaces and bare soil.

7. Conclusion and discussions

High spatial resolution remote sensing imagery (e.g. IKONOS and Quickbird) provides detailed information about urban features, thereby offering great potential...
for large-scale urban analysis, such as building structure extraction, impervious surface estimation, etc. The improved spatial resolution, however, leads to reduced boundary effects and increased within-class variability, therefore bringing challenges for spectral analysis. This paper analysed the spectral characteristics of high-resolution remote sensing imagery, IKONOS MSI, and evaluated whether a popular impervious surface estimation method, spectral mixture analysis, can be applied to high spatial resolution remote sensing imagery. In particular, this paper analysed the reduced boundary effects (mixed or pure pixel problem) and within-class variation issues associated with IKONOS MSI imagery, and developed an SMA model with interior end-member set and spectral normalization to address these problems. Analysis of results suggests several conclusions.

First, by analysing the spectral characteristics of the IKONOS image, the reduced boundary effects (more pure pixels) and increased within-class variability were observed. In particular, for the Village of Grafton and the Town of Grafton, the proportions of pure impervious surface pixels to all pixels containing impervious surfaces are 52.0% and 56.8%, respectively. This suggests that although a sub-pixel analysis is still a valid option for impervious surface estimation, such analysis must take the pure pixels into consideration. Moreover, for the pure impervious surface pixels of IKONOS imagery, there exists a large within-class spectral variation. In fact, the coefficients of spectral variation for a pure impervious surface range from 27% to 58%. Furthermore, the feature space plots of MNF components also indicate highly different spectral characteristics for pure impervious surface pixels.

Secondly, the interior end-member set selection and spectral normalization can partially address the issues of boundary effects and within-class variability. In particular, with a set of interior end-members, pixels located within the inner space enclosed by the interior end-members are linearly unmixed, and the pixels located outside the inner space (mostly pure pixels) are proportionally unmixed to the one (or two) closest end-member(s). Therefore, pure pixels, which are located outside the inner space, are likely to receive a fraction value of 100%. In addition, spectral normalization significantly reduces the coefficients of spectral variation. Taking the impervious surface class as an example, with the spectral normalization, the coefficients of spectral variation were reduced by approximately 17–20% for IKONOS bands 1, 2 and 3, and 11% for band 4.

Finally, comparing the four SMA models, we found that the model with interior end-member set and spectral normalization performs significantly better than the other three models. While this model slightly overestimates the overall impervious surface areas for the entire study area (SE=2.66%), for the pixel-wise comparison, it performs reasonably better than the other three models with the lowest MAE for the entire study area (9.2%), the Town of Grafton (20.0%) and the Village of Grafton (6.9%).

Although the SMA with interior end-member set selection and spectral normalization outperforms other SMA methods, future improvements are still necessary. One issue is associated with the difficulty of interior end-member set selection. As discussed in this paper, interior end-member set selection is somewhat arbitrary, and the results of impervious surface estimates may be highly sensitive to different end-member sets (Song 2005). The other problem involves the mis-registration between IKONOS and aerial photographs, and the misclassification of aerial photographs. For a pixel-wise comparison, even a minor spatial mis-registration or misclassification may make the results unreliable. This may partially explain the low impervious surface
estimation accuracy at the per-pixel level, and the significant improvements with the increments of measurement sizes. Moreover, although this model was applied successfully to the Town and Village of Grafton, WI, USA, it remains uncertain whether similar results can be obtained using different remote sensing data sets and/or applied to different geographical regions. The biophysical compositions of an urban area (e.g. different types of soil, vegetation and impervious surfaces) may have significant influences on the modelling results, and the confusion between impervious surfaces and bare soil remains a major obstacle for urban analyses. A global comparative analysis (e.g. Small 2005) would be helpful to examine the reliability of model performance. Moreover, the integration of this model with spatial analytical techniques (e.g. spatial segmentation, fractal analysis) may also be able to improve the accuracy of impervious surface estimation.

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**References**


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