Segmentation-based and rule-based spectral mixture analysis for estimating urban imperviousness

Miao Li\textsuperscript{a}, Shuying Zang\textsuperscript{a,*}, Changshan Wu\textsuperscript{b,c}, Yingbin Deng\textsuperscript{c}

\textsuperscript{a} Key Laboratory of Remote Sensing Monitoring of Geographic Environment, College of Heilongjiang Province, Harbin Normal University, Harbin 150025, China
\textsuperscript{b} Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, No. 9 Dengzhuang South Road, Haidian District, 100094 Beijing, China
\textsuperscript{c} Department of Geography, University of Wisconsin-Milwaukee, Milwaukee, WI 53201, USA

Received 21 July 2014; received in revised form 2 December 2014; accepted 9 December 2014

Abstract

For detailed estimation of urban imperviousness, numerous image processing methods have been developed, and applied to different urban areas with some success. Most of these methods, however, are global techniques. That is, they have been applied to the entire study area without considering spatial and contextual variations. To address this problem, this paper explores whether two spatio-contextual analysis techniques, namely segmentation-based and rule-based analysis, can improve urban imperviousness estimation. These two spatio-contextual techniques were incorporated to a classic urban imperviousness estimation technique, fully-constrained linear spectral mixture analysis (FCLSMA) method. In particular, image segmentation was applied to divide the image to homogenous segments, and spatially varying endmembers were chosen for each segment. Then an FCLSMA was applied for each segment to estimate the pixel-wise fractional coverage of high-albedo material, low-albedo material, vegetation, and soil. Finally, a rule-based analysis was carried out to estimate the percent impervious surface area (%ISA). The developed technique was applied to a Landsat TM image acquired in Milwaukee River Watershed, an urbanized watershed in Wisconsin, United States. Results indicate that the performance of the developed segmentation-based and rule-based LSMA (S-R-LSMA) outperforms traditional SMA techniques, with a mean average error (MAE) of 5.44% and $R^2$ of 0.88. Further, a comparative analysis shows that, when compared to segmentation, rule-based analysis plays a more essential role in improving the estimation accuracy.

© 2014 COSPAR. Published by Elsevier Ltd. All rights reserved.

Keywords: Linear spectral mixture analysis; Segmentation-based analysis; Rule-based analysis; Urban imperviousness

1. Introduction

The increase of urban impervious surface coverage in a watershed has received significant attentions recently (Arnold and Gibbons, 1996). Generally, when the percent impervious surface area (%ISA) coverage reaches 10% or higher, water quality degradation can be detected, and apparent degradation has been found when the %ISA within a watershed approaches 30% (Arnold and Gibbons, 1996). The existence of a significant amount of urban impervious surfaces in a watershed can result in an “urban stream syndrome” with increased hydro-period variability and degradation of water quality (Meyer et al., 2005). Therefore, accurate estimation of urban imperviousness is essential for watershed management and planning.

Recently, %ISA information has been estimated using remote sensing techniques, including manual digitization or automatic image processing. With automatic image pro-
cessing techniques, such as artificial neural network, regression tree, regression analysis, and linear spectral mixture analysis (LSMA), %ISA has been extracted from medium- and coarse-resolution remotely sensed data with some success (Weng, 2012). Within them, LSMA has proven successful in mapping urban imperviousness in urban areas (Wu and Murray, 2003; Weng, 2012). LSMA assumes that the spectra of a mixed pixel is a linear summation of the spectra of each pure land cover (e.g. endmember) within that pixel, weighted by percent areal cover (Roberts et al., 1998). For Urban environments, Ridd (1995) developed a vegetation–impervious surface–soil (V–I–S) model, which assumes that each pixel in an urban/suburban area is composed of three basic land cover types, namely vegetation, impervious surfaces, and bare soil. When applied to satellite remote sensing imagery, however, impervious surfaces have rarely been considered as an individual endmember as they include a large number of materials with significantly different spectra. To address this problem, Wu and Murray (2003) developed a vegetation-high albedo-low albedo-soil (V-H-L-S) model to characterize urban environments of Columbus, OH, United States, and found that urban impervious surfaces can be estimated through summing the fractional covers of high albedo and low albedo materials. Recently, Zhang et al. (2014) applied a high albedo-low albedo-vegetation (H-L-V) model to estimate %ISA in high-density urban areas, and a high albedo-low albedo-vegetation-soil (H-L-V-S) model to quantify %ISA in low-density urban areas.

Although a variety of LSMA models have been developed for accurate estimation of %ISA. Several problems still exist. One major problem is the selection of endmember classes and their corresponding spectra. In urban areas, for example, major endmember classes include high-albedo materials, low-albedo materials, vegetation, and soil. High-albedo materials, however, may include clouds, metals, concrete, glass, dry soil, and/or sand, etc., and low-albedo materials may include asphalt, shade, moist soil, water, etc. To address this problem, a number of techniques, including normalized spectral mixture analysis (NSMA), derivative spectral unmixing (DSU), and weighted spectral mixture analysis (WSMA), segment-based spectral mixture analysis (MESMA), have been developed (Somers et al., 2011; Feizizadeh and Blaschke, 2013). All of these techniques, however, can be categorized as global techniques, without considering spatio-contextual variations. Spatio-contextual information, however, has proven essential in remote sensing image classification, information extraction, and change detection applications (Atkinson and Naser, 2010; Moser et al., 2013). Although important, spatio-contextual techniques have been rarely incorporated into LSMA for estimating %ISA (Shi and Wang, 2014). Several exceptions include the spatially adaptive spectral mixture analysis (SASMA) and prior-knowledge-based spectral mixture analysis (PKSMA) (Deng and Wu, 2013; Zhang et al., 2014), and spatial spectra mixture analysis (Shi and Wang, 2014). This research explores whether two spatio-contextual analysis techniques, (1) segmentation-based analysis and (2) rule-based analysis, can provide a better selection of endmember classes and their spectra, and further improve the accuracy of %ISA estimates. Specifically, image segmentation was initially applied to divide a remote sensing image into a number of homogeneous segments, and within each segment, the types and spectra of each endmember classes were selected. With the segment-based endmembers, an LSMA was then applied for each individual segment. With the resultant fractional values of each endmember, a rule-based analysis was applied to derive the %ISA. The advantages of the proposed segmentation-based and rule-based LSMA (S-R-LSMA) method lie in its ability to better incorporating spatio-contextual information in addressing spectral and spatial variability issues associated with LSMA.

2. Study areas and data

Milwaukee River Basin, Wisconsin, United States has been selected as the study area for this research (see Fig. 1). Milwaukee River Basin is located in Southeastern Wisconsin along Lake Michigan, and covers a geographical area of 2280 km². Within the basin, urban land covers (Milwaukee City) can be found in the southern portion, and rural land covers, including forest lands, planted/cultivated lands, open water, and wetlands, dominate the northern part.

A Landsat Thematic Mapper (TM) image acquired on November 6, 2001 was employed in this study. This image has a spatial resolution of 30 m and 7 multispectral bands. In addition to the Landsat image, aerial photographs acquired in 2001 were obtained for assessing the model performances. These two datasets were obtained from the American Geographical Society Library (AGSL) at University of Wisconsin-Milwaukee. All of these datasets were re-projected to the Universal Transverse Mercator (UTM) projection with a datum of World Geodetic System 84 (WGS84).

3. Methods

To incorporate spatio-contextual information into LSMA, we implement the S-R-LSMA method, which consists four steps, including (1) Image pre-processing, (2) image segmentation and segment-based endmember extraction, (3) fully-constrained LSMA, and (4) rule-based analysis. The diagram of these steps is illustrated in Fig. 2.

3.1. Image preprocessing

In order to carry out the S-R-LSMA model, a prerequisite step is to pre-process the acquired images. First, we performed an atmospheric correction using the ATCOR module provided by ERDAS Imagine, a commercial remote sensing image processing program. Results indicated that no atmospheric correction was necessary due...
to the cloud-free atmospheric condition of the study area. Second, we examined the geometric accuracy of the TM image and aerial photos. Results indicate that TM image is within a geometric error of 15 m, and the aerial photos are within a geometric error of 12 m. Therefore, no further geometric rectification was performed. Finally, we converted the digital number (DN) values of the TM image to normalized exo-atmospheric reflectance measures using the radiance to reflectance conversion equations provided by the Landsat TM 5 handbook.

For a better extraction of urban impervious surfaces, water body has been identified and masked with the help of modified normalized difference water index (MNDWI) proposed by Xu (2006). The formula of MNDWI can be expressed as follows.

\[
\text{MNDWI} = \frac{\text{Green} - \text{MIR}}{\text{Green} + \text{MIR}} \quad (1)
\]

where Green represents the reflectance of Green Band (Band 2), and MIR indicates the reflectance of mid-infrared band (Band 5).

### 3.2. Image segmentation and segment-based endmember extraction

Image segmentation has been typically applied to perform object-based image classification (Blaschke, 2010). In this research, the purpose of segmentation is not to divide the image into the smallest “objects”, but to derive homogeneous regions. A basic assumption is that land cover types are homogeneous within a region, and therefore an individual LSMA can be performed for each region. To implement image segmentation, we employed the multi-resolution image segmentation (MRS) algorithm available in E-cognition, a commercial software package (Benz et al., 2004). The MRS algorithm uses a bottom-up region merging algorithm that begins with pixel sized objects, which iteratively grow through merging smaller objects into larger ones with a uniform scale, shape, compactness, and spatial and spectral homogeneity. Scale, shape, and compactness are three main parameters of segmentation. Especially, the scale parameter determines the size of image segments, and lower scale values are associated with smaller image segments, while higher values result in larger segments (Benz et al., 2004; Myint et al., 2011). In addition, shape parameter controls the textural...
homogeneity of segments, and an appropriately chosen shape parameter can avoid the creation of irregular segments (e.g. slivers). Similarly, the compactness parameter controls the ratio between edge length of a segment and its geographic area (Benz et al., 2004). Although these three parameters have been often applied in the MRS algorithm, there has not been a consensus on selecting best values for segmentation. In this study, therefore, we employed a trial-and-error approach to segment the image into 2, 10, and 20 objects using three scale levels (e.g. 600, 430, and 280), a compactness of 0.2, and a shape parameter of 0.5.

With each segmented image, an individual endmember extraction technique was applied to extract endmember spectra respectively. In particular, a minimum noise fraction (MNF) transformation was performed to convert the reflectance images to MNF components. Then scatterplots of MNF components were drawn to identify the corresponding endmembers, including low-albedo materials, high-albedo materials, soil, and vegetation. Specifically, endmember spectra were identified on the vertices of the spectral plots of MNF components, and confirmed through visualizing the aerial photos. For details of this endmember extraction method, readers can refer to Wu and Murray (2003). With the individual endmember extraction technique applied to each image segment, endmember classes and their spectra were derived.

### 3.3. Linear spectral mixture analysis (LSMA)

LSMA assumes the spectrum of a mixed pixel can be modeled by the spectra of each endmember weighted by their areal abundance. In this research, a fully constrained LSMA (see Eq. (2)) was implemented for each individual image segment.

\[
R_i = \sum_{k=0}^{n} f_k R_{ik} + e
\]

Subject to \( \sum_{k=0}^{n} f_k = 1, \quad 0 \leq f_k \leq 1 \)

where \( R_i \) is the spectral reflectance of band \( i \) of a pixel; \( k \) represents a particular endmember class; \( n \) is the total number of endmembers; \( f_k \) is the fraction of endmember \( k \) within a pixel; \( R_{ik} \) is the spectral reflectance of endmember \( k \) within the pixel in band \( i \); \( e \) is the modeling error. With LSMA, the areal fraction of each endmember can be derived through an inverse least squares deconvolution method.

### 3.4. Rule-based endmember extraction

Through applying the above LSMA method to each image segment, areal fractions of four endmember classes, low-albedo, high-albedo, soil, and vegetation, were obtained. We further examined the compositions of high-albedo and low-albedo materials in different segments, and found that, in urbanized segments, high-albedo materials are mostly associated with commercial and transportation land uses, while low-albedo materials are associated with asphalt. In rural segments, however, low-albedo materials are associated with dark soil, shade, and even some mis-identified water pixels. To address this problem, we developed a rule-based analysis to correct the errors caused by the mis-interpreted low-albedo materials. In this study, we employed a straightforward approach, that is, for a segment with more than 10% of high-albedo materials, \%ISA is calculated as the summation of percent high-albedo and percent low-albedo materials. On the contrast, if the percent of high albedo materials in a segment is less than 10%, we consider that impervious surfaces only include high-albedo materials, and low-albedo materials are considered as pervious (e.g. rural) land covers. The criterion of 10% is created based on a trial-and-error approach, with which both visual inspection and quantitative analysis were applied. For the trial-and-error approach, 100 randomly selected sampling pixels have been selected to examine the impervious surface estimation accuracy with different criteria. We acknowledge that we only employed a straightforward approach, and more complicated rule-based analysis, such as regression tree and random forest, may generate better results.

### 3.5. Accuracy assessment and comparative analysis

In order to assess the performance of the S-R-LSMA method, 200 randomly selected samples were employed. A neighborhood size of 3 x 3 pixels (90 x 90 m) has been adopted to reduce the impact of geometric error (Deng and Wu 2013; Powell et al. 2007). The geometric errors of the TM and aerial photos are within 12 m and 15 m, and the 3 x 3 sampling size can effectively reduce the estimation error due to geometric mismatch. For every sample, the corresponding “actual” geographic area of impervious surfaces was manually digitized through visually interpreting the aerial photos and the \%ISA was calculated through dividing the impervious surface area by the sample area (e.g. 8100 m²). With the “actual” and modeled \%ISA, two error measurement metrics, mean absolute error (MAE) and systematic error (SE), were employed to evaluate the modeling accuracy. Within them, MAE measures the precision, and SE examines the bias of the model. Especially, MAE indicates the average difference between the modeled \%ISA and the “actual” \%ISA, and SE measures whether the model over- or under-estimate the \%ISA. The formula of MAE and SE are given by Eqs. (3) and (4) respectively.

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |f_i - y_i|
\]

\[
\text{SE} = \frac{1}{n} \sum_{i=1}^{n} (f_i - y_i)
\]
where $f_i$ is the modeled %ISA of pixel $i$, $y_i$ is the actual %ISA of pixel $i$, and $I$ is the number of samples.

In addition to the developed S-R-LSMA model, we also carried out three additional LSMA models for comparative purposes (see Table 1). The first model is a global model, named LSMA, with which endmember spectra were chosen based on the entire image, and the impervious surface fraction was calculated as the summation of the percent of low- and high-albedo materials. The second one is the segment-based model (S-LSMA) without the rule-based decision analysis. That is, endmember spectra were selected based on each individual segment, but the impervious surface fraction was calculated as the summation of low- and high-albedo materials. The third model is a rule-based model (R-LSMA), with which globally chosen endmembers were applied to the entire image, but the decision rules were applied to each segment.

### 4. Results

The resultant image segmentation results with 2, 10, and 20 segments are shown in Fig. 3. Visual inspection of these figures indicates that the segments are appropriately delineated as each segment is composed of relatively homogeneous land covers, while heterogeneous land covers are found in different segments.

With segmented images, segment-based endmember extraction technique was applied to the images with 2, 10, and 20 segments. Although all of these three segmentation techniques were applied, we performed detailed analyses with 10 segments as a trade-off between computational burden and model performance. Fig. 4 shows the scatterplots of the first three MNF components associated with 10 segmented images (e.g. segment #2, #5, and #10). It indicates that although the shapes of these scatterplots are similar, obvious differences can be discerned, indicating the necessity of identifying endmember spectra for each individual segment. The chosen endmember spectra (see Fig. 5) also indicate modest variations. These indicate the necessity of employing the segmentation-based analysis to address the spatial varying issue of endmember spectra.

With the segmentation-based analyses, the extracted endmembers were inputted to the LSMA technique to measure the fractional coverage of low-albedo materials, high-albedo materials, vegetation, and soil. Then the rule-based analysis was applied to generate the final %ISA map (see Fig. 6A). Visual inspection indicates the S-R-LSMA performs well in estimating %ISA, as higher %ISA values can be found in commercial and residential areas, and significantly lower %ISA values can be found in agriculture, forestry, and wetlands. Quantitative assessment shows consistent results. Taking the analysis with 10 segments as an example, the performance of the S-R-LSMA is satisfactory, with an MAE of 5.44%, SE of 2.06%, and $R^2$ of 0.88 (see Table 2). Further, a comparative analysis among 2, 10, and 20 segments shows that no significant performance difference can be identified. For example, although the S-R-LSMA models with 10 and 20 segments are with slightly lower MAE and higher $R^2$ values, they also have...

<table>
<thead>
<tr>
<th>Segmentation-based analysis</th>
<th>Rule-based analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>S-R-LSMA</td>
<td>✓</td>
</tr>
<tr>
<td>LSMA</td>
<td>×</td>
</tr>
<tr>
<td>S-LSMA</td>
<td>✓</td>
</tr>
<tr>
<td>R-LSMA</td>
<td>×</td>
</tr>
</tbody>
</table>

Table 1 Linear spectral mixture analysis (LSMA) models for estimating %ISA (S-R-LSMA: segment-based and rule-based LSMA, S-LSMA: segment-based LSMA, R-LSMA: rule-based LSMA).

Fig. 3. Results of image segmentation using the multi-resolution image segmentation (MRS) technique provided by the e-Cognition program. For generating (A) 2 segments, (B) 10 segments, and (C) 20 segments, scale levels of 600, 430, and 280 were applied respectively, together with a compactness of 0.2, and a shape parameter of 0.5.
relatively higher SE values. This observation indicates that a large number of segments (e.g. a high scale value) may not result in a better accuracy. Instead, in this study, the S-R-LSMA model with 2 segments (urban v.s. rural) has produced satisfactory results.

For a comparative analysis, LSMA, S-LSMA, and R-LSMA were also performed, and the results are reported in Fig. 6 and Table 2. Analyses of results indicate that the performances of LSMA and S-LSMA are much worse than that of S-R-LSMA. In particular, with LSMA, the MAE of %ISA has a value of 9.70%, showing a relatively large estimation error. In addition, the SE has a value of 8.03%, indicating obvious over-estimation of %ISA, especially in rural areas. Similar, but slightly better results have been obtained with the S-LSMA method. Finally, the performance of R-LSMA is comparable, though modestly worse, when compared to the S-R-LSMA. While R-LSMA is with similar MAE values when compared to S-R-LSMA, it does have a much higher SE value, indicating an obvious over-estimation.

5. Discussion

5.1. Segment-based endmember extraction

Spatial variations of endmember spectra are considered essential with LSMA (Shi and Wang, 2014). With the traditional LSMA method, one single spectrum of each endmember is chosen and applied to the entire image. Such a method may inevitably bring the problem of endmember variability (Somers et al., 2011). Segment-based analysis developed in this paper, therefore, incorporates spatial information into endmember selection, and has potential to address the issues of endmember variability. Results from this research indicate that the performance of S-LSMA is modestly better than that of LSMA. Further, a
comparative analysis of S-R-LSMA and S-LSMA with different numbers (e.g. 2, 10, and 20) of segments shows that the number of segments may not be crucial as similar performance has been obtained. Specifically, the model with only two segments, urban and rural segments, has produced similar results when compared to its counterparts with 10 and 20 segments. Further studies, however, are necessary to confirm this observation.

5.2. Rule-based analyses

Due to the complexity of impervious surfaces, many studies have employed low-albedo materials and high-albedo materials as endmembers, and later calculated %ISA as the summation of the fractions of these two endmembers. Such an analysis might be appropriate for urbanized areas. In rural areas, however, low-albedo materials may be water, shades, bare soil, etc., and severe over-estimation of %ISA might be a major concern. The rule-based analysis developed in this paper has incorporated contextual knowledge into the analysis. That is, with a simple rule, the performance of %ISA estimation can be significantly improved. Although the selection of the decision rule (e.g. 10% of high-albedo materials) was obtained from a trial-and-error approach, it does represent the difference between urban and rural land uses. That is, urban areas are with a high proportion of high-albedo (e.g. building roofs) and low-albedo (e.g. asphalt) materials, both of which can be categorized as impervious surfaces. In rural areas, on the contrary, the proportion of high-albedo materials is much less, and low-albedo materials are likely to be wet soil, shade, etc. Therefore, this rule-based analysis successfully identified the different compositions of low-albedo materials through incorporating contextual knowledge. This is consistent with the findings reported by Zhang et al. (2014), who employed different LSMA models for urban and rural areas.

5.3. Spatio-contextual based LSMA and MESMA

Due to the landscape heterogeneity of urban and suburban areas, the global LSMA may be inappropriate for an accurate estimation of urban impervious surfaces. Spatio-contextual based LSMA and MESMA, therefore, have emerged as better alternatives to global LSMA approaches. Although both approaches can be considered as “local” approach, with which each pixel is modeled with different number, type, and spectra of endmember classes. Both approaches acknowledge endmember variability, and attempt to accommodate the variability. Their major difference, however, lies in the rationales of these choices. Spatio-contextual based LSMA employed spatial autocorrelation analysis (e.g. segmentation based analysis) and contextual knowledge (e.g. rule-based analysis) for better selecting endmembers. MESMA, on the contrary, collects a large number of endmembers to form a spectral library,
then selects the best LSMA model through analyzing modeling errors (Roberts et al., 1998; Powell et al., 2007). Although we did not perform an MESMA approach, we acknowledge that a comprehensive comparative analysis of these two groups of approaches is essential for future research.

Table 2
Performances of the four linear spectral mixture analysis (LSMA) models, including segment-based and rule-based LSMA (S-R-LSMA), LSMA, segment-based LSMA (S-LSMA), and rule-based LSMA (R-LSMA). For each model, mean average error (MAE), systematic error (SE), and squared correlation coefficient are presented. For S-R-LSMA and S-LSMA models, results with 2, 10, and 20 segments are also shown.

<table>
<thead>
<tr>
<th>Segment #</th>
<th>S-R-LSMA</th>
<th>LSMA</th>
<th>S-LSMA</th>
<th>R-LSMA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>10</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>MAE</td>
<td>5.70</td>
<td>5.44</td>
<td>5.55</td>
<td>9.70</td>
</tr>
<tr>
<td>SE</td>
<td>1.86</td>
<td>2.06</td>
<td>2.27</td>
<td>8.03</td>
</tr>
<tr>
<td>R²</td>
<td>0.85</td>
<td>0.88</td>
<td>0.88</td>
<td>0.88</td>
</tr>
</tbody>
</table>

6. Conclusions

The quantification of impervious surface area in a watershed is essential for watershed management and planning. This paper proposed an improved linear spectral mixture analysis (S-R-LSMA) technique for estimating...
sub-pixel urban impervious surface cover through integrating image segmentation and rule-based analysis techniques. The developed technique was applied to a Landsat TM image acquired in Milwaukee River Watershed, an urbanized watershed. Analyses of results suggest two major conclusions.

First, the developed S-R-LSMA method outperforms all three other LSMA methods, with a mean average error (MAE) of 5.44%, SE of 2.06%, and $R^2$ of 0.88. This indicates that the integration of segmentation-based and rule-based analyses can significantly improve the LSMA model in estimating %ISA.

Second, when compared to segment-analysis, rule-based analysis plays a more important role in improving the estimation accuracy of %ISA. With the rule-based analysis, the over-estimation of %ISA in rural areas has been effectively addressed, and therefore the overall %ISA estimation accuracy has been improved significantly.

Acknowledgements

This study was financially supported by the National Natural Science Foundation of China (no. 41030743; no. 41171322), Graduate Innovative Programs Foundation of Harbin Normal University (No.HSDBSCX2014-02), University of Wisconsin-Milwaukee Graduate School. The authors would like to thank anonymous reviewers for their constructive comments on earlier drafts of this manuscript.

References


