Modified multiple endmember spectral mixture analysis for mapping impervious surfaces in urban environments

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Abstract. A modified multiple endmember spectral mixture analysis (MMESMA) approach is proposed for high-spatial-resolution hyperspectral imagery in the application of impervious surface mapping. Different from the original MESMA that usually selects one endmember spectral signature for each land-cover class, the proposed MMESMA allows the selection of multiple endmember signatures for each land-cover class. It is expected that the MMESMA can better accommodate within-class variations and yield better mapping results. Various unmixing models are compared, such as the linear mixing model, linear spectral mixture analysis using the original linear mixture model, original MESMA, and support vector machine using a nonlinear mixture model. Airborne 1-m resolution HySpex and ROSIS data are used in the experiments. For HySpex data, validation based on 25-cm synchronism aerial photography shows that MMESMA performs the best, with the root-mean-squared error (RMSE) of the estimated abundance fractions being 13.20% and the correlation coefficient ($R^2$) being 0.9656. For ROSIS data, validation based on simulation shows that MMESMA performs the best, with the RMSE of the estimated abundance fraction being 4.51% and $R^2$ being 0.9878. These demonstrate that the proposed MMESMA can generate more reliable abundance fractions for high-spatial-resolution hyperspectral imagery, which tends to include strong within-class spectral variations. © 2014 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.JRS.8.085096]

Keywords: urban remote sensing; impervious surface mapping; modified multiple endmember spectral mixture analysis; high-spatial-resolution image; hyperspectral image.

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1 Introduction

Remote sensing is an important technique for land-cover land-use mapping in urban environments. Some researchers applied multifeature methods for urban information extraction. Particularly, many studies of urban remote sensing have focused on impervious surface mapping. Impervious surfaces, such as roads, driveways, parking lots, rooftops, etc., are anthropogenic objects where water cannot infiltrate into soils. As impervious covers are increased in developing urban environments, forest and grass covers are gradually decreased. The percentage of land covered by impervious surfaces impacts the urban ecosystem. Therefore, studying impervious surface is of great importance to the human settlement environment and sustainable development of the environment.

Various linear and nonlinear models of impervious surfaces have been proposed in urban remote sensing studies, including methods based on linear spectral unmixing, artificial neural networks, support vector machine, and regression trees. Linear spectral mixture analysis

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(LSMA) is the most widely used technique.11–13 This approach finds spectrally unique signatures of pure ground components, called endmembers, and decomposes mixed pixels as linear combinations of these endmembers.14 Due to the fact that the endmembers participating in a specific mixed pixel construction may be varied, a novel and effective multiple endmember SMA (MESMA) was developed,15 which searches the optimal endmember set per pixel to achieve the best unmixing performance. MESMA has been used in various applications, including the mapping of forests and natural land-cover types,16,17 impervious surfaces,18 mapping burn severity,19 etc. In an impervious surface context, Yang et al. presented a variant of MESMA for estimating the impervious surface area fractions in Lake Kasumigaura Basin, Japan. MESMA was examined in a subpixel analysis of Landsat Thematic Mapper imagery to map three physical components of urban land cover: impervious surface, vegetation, and soil.20 Yougentob et al.21 improved the performance of MESMA in mapping nine eucalypt tree species. In those approaches, the result of spectral unmixing at lower levels of complexity was applied to constrain the definition of MESMA models at higher complexity levels, thus eliminating the possible confusion between spectrally similar objects belonging to different land-cover classes. Overall, the MESMA approach is effective in mapping and monitoring urban land-use/land-cover changes.

With the development of hyperspectral imaging sensors, more opportunities are provided for urban environment monitoring by using high-spatial-resolution hyperspectral imagery, where multiple endmember signatures may exist to represent an object class due to strong within-class variations. The traditional LSMA restricts the model to the use of one spectrum for each endmember class;22 as a result, it may not incorporate spectral variations in nature. In the original MESMA, one spectral signature is selected for each land-cover class. In this paper, we will propose a modified MESMA (MMESMA) to allow multiple spectral signatures to be selected for each endmember class to better accommodate within-class spectral variations. Its performance in impervious surface mapping using high-spatial-resolution hyperspectral imagery collected by the HySpex and ROSIS imaging sensors will be investigated.

The remainder of this paper is organized as follows. Section 2 describes the study area, the data sets used in this study, and the main preprocessing steps. Section 3 presents the proposed unmixing method, the endmember selection procedure, and validation approaches. The unmixing results, their validation, and the possibilities to operationally use the MMESMA algorithm to map impervious surfaces are discussed in Sec. 4. Finally, Sec. 5 summarizes the main findings and highlights the advantages and limitations of the proposed approach.

2 Data and Study Area

2.1 HySpex Data

The airborne hyperspectral data have been collected using a HySpex VNIR-1600 and SWIR-320 m sensor from Norsk Elektro Optikk (Oslo, Norway) AS. The HySpex sensor operates from the visible to shortwave infrared spectral range (0.4 to 2.5 μm) and collects up to 408 spectral bands with an average band width of 3.7 nm/5 nm and 14-bit digitization. The sensor uses a charge coupled device (CCD) array (HgCdTe detector) with 459 × 5844 elements and a pixel size of 1 m. These data were acquired in Oland, Sweden, during the summer of 2011. Oland is the second largest Swedish island and is the smallest of the traditional provinces of Sweden. Oland has an area of 1342 km² and is located in the Baltic Sea just off the coast of Smaland. It is separated from the mainland by the Kalmar Strait and is connected to it by the 6 km Oland Bridge. Because of the dropouts and vertical striping generated during the image acquisition process and the section of area, the test data, as shown in Fig. 1, include 320 × 800 elements. 363 bands were extracted from the original image.

2.2 ROSIS Data

These data were acquired by the ROSIS sensor during a flight campaign over Pavia, northern Italy.
3 Methodology

3.1 MESMA

LSMA assumes that the reflectance of a pixel is a linear combination of the spectra of all endmembers within the pixel.\(^2\)\(^3\)\(^4\) The model can be expressed as\(^5\):

\[
R_i = \sum_{k=1}^{n} f_k R_{ik} + \epsilon_i;
\]

where \(R_i\) is the spectral reflectance of band \(i\) of a pixel, \(f_k\) is the fraction of endmember \(k\) within the pixel, \(R_{ik}\) is the spectral reflectance of endmember \(k\) with the pixel of band \(i\), and \(\epsilon_i\) is the residual for band \(i\).

When each endmember reflectance in different spectral bands is known, fractions in Eq. (1) can be estimated with a least-squares solution. Due to simplicity, LSMA has been widely adopted. However, it assumes that the numbers and types of endmembers for all pixels are the same; in reality, a pixel may only contain several land-cover classes, which means the numbers and types of endmembers may change per pixel. It has been found that using the endmembers that actually participate in the composition of a pixel can yield a better unmixing performance.\(^6\) The original MESMA extends LSMA by allowing the numbers and types of endmembers to vary on a per-pixel basis. Each pixel tests multiple models, which are combined with different combinations of endmembers, and the best-fit model for unmixing is selected. It has been shown to work well for unmixing medium and low-spatial-resolution images.

However, in the original MESMA, the candidate models are constructed by different land-cover types with each land-cover type consisting of one or more endmember signatures, but only one is selected. Thus, it may overlook the spectral variation inherent in the same land-cover type. This could be problematic, particularly to images with high spatial and spectral resolutions, where within-class variations may be profound.

3.2 MMEsMA

To demonstrate the concept that multiple endmember signatures with each land-cover class may be used for unmixing, an experiment with the HySpex data was carried out. There are nine endmember signatures contained in four land-cover types. It was assumed that the number

---

Fig. 1 Location of the study area and spatial extent of the HySpex imaging spectrometer data set (false color composite).
of endmembers within a pixel were less than four but without the restriction of their land-cover type. Each model was tested by each pixel to select the best-fit model for unmixing. Then nine regions in Fig. 2 were selected to compute the best-fit models, which include 52% pixels of the test data.

Table 1 shows P2 as the proportion of the selected models that have at least two endmember signatures belonging to the same land-cover type to all the models. Obviously, the majority of the best-fit models have multiple endmembers belonging to the same land-cover type.

Therefore, we hereby propose the MMESMA to better accommodate within-class variations. The basic idea is to build candidate models based on land-cover classes, but for each land-cover class, use all the available endmember signatures for unmixing. For an image scene with four land-cover classes, there will be four 1-class models, six 2-class models, and four 3-class models. Since there will be no further endmember searching within each class, the overall computational cost can also be greatly reduced. Note that endmember variability was incorporated into the mixture analysis by representing each endmember by a bundle of spectra, each of which could reasonably be the reflectance of an instance of the endmember in Ref. 24. However, the original LSMA was adopted.

Similar to MESMA, MMESMA uses the root mean square of the residual error (RMSRE) to measure the goodness of fit of each candidate model, which is defined as

\[
\text{RMSRE} = \sqrt{\frac{\sum_{i=1}^{m} (\epsilon_i)^2}{m}},
\]

where \( m \) is the number of bands and \( \epsilon_i \) is the residual error for each band \( i \).

Fig. 2 Location of nine sample regions.
After calculating RMSRE, other criteria would be used to determine the most appropriate model. The criteria used by Demarchi et al.27 in their study mapping impervious surfaces in urban and suburban environments will be adopted in MMESMA, which is described as follows:

1. The lowest RMSRE of all candidate models with different numbers of land-cover types is calculated with Eq. (2).

2. The relative decrease (DECR) in RMSRE between the models whose number of land-cover types differs by one is calculated as follows:

   \[
   \text{DECR} = \frac{\text{RMSRE}_n - \text{RMSRE}_{n+1}}{\text{RMSRE}_n} \times 100, \tag{3}
   \]

   where \( n \) is the number of land-cover types used for each model, RMSR \( E_n \) is the lowest RMSRE value of all possible \( n \) land-cover type models, and RMSR \( E_{n+1} \) is the lowest RMSRE value of all possible \( n + 1 \) land-cover type models.

3. If the relative decrease in RMSRE (DECR) is more than a predefined threshold, the model with more land-cover types is selected as the best-fit model and is used to unmix the corresponding pixel.

### 3.3 Endmember Selection

In urban environments, land-cover types can be characterized by the V-I-S model proposed by Ridd28 and an impervious surface (I) can be categorized as high albedo, low albedo, or some combination.29 The high albedo mainly refers to the buildings and roads that have high reflectance, such as the houses with a red roof and metal. The low albedo is mainly the surfaces with low reflectance, including the houses with a gray roof and asphalt. Considering the shadows of buildings and trees are widely distributed, shadow is defined as an additional type.

There are two major techniques with which to find the endmember spectral signatures to be used. The first one gains endmember signatures from spectral libraries. Reference endmembers can be derived from the field or a laboratory condition. Another obtains spectra derived from the image itself. This research adopted the latter because the spectra can reflect in-field spectral variations. To deal with high data dimensionality, a maximum noise fraction (MNF) transform was applied,30,31 and the first three MNF components were used to select endmembers due to the fact that most information was contained in the first few MNF components. Then we applied the algorithm of a pure pixel index to extract the most spectrally pure pixels in the image. The pixels were plotted in the feature space by using \( n \)-dimensional visualization and pixels belonging to

<table>
<thead>
<tr>
<th>Area</th>
<th>P2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region 1</td>
<td>0.45</td>
</tr>
<tr>
<td>Region 2</td>
<td>0.51</td>
</tr>
<tr>
<td>Region 3</td>
<td>0.55</td>
</tr>
<tr>
<td>Region 4</td>
<td>0.78</td>
</tr>
<tr>
<td>Region 5</td>
<td>0.50</td>
</tr>
<tr>
<td>Region 6</td>
<td>0.56</td>
</tr>
<tr>
<td>Region 7</td>
<td>0.55</td>
</tr>
<tr>
<td>Region 8</td>
<td>0.54</td>
</tr>
<tr>
<td>Region 9</td>
<td>0.69</td>
</tr>
</tbody>
</table>
the same endmember in level 3 are clustered together, so the endmember spectra could be obtained by referencing the 0.25-m image.

Detailed information about endmembers in the HySpex data is shown in Table 2. Level 1 corresponds to three major land-cover types and shadow, and level 2 indicates the specific land-cover components that were used to construct the candidate models. Two, three, or all four land-cover components and shadow may be combined to construct a model, in which all the endmembers in level 3 correspond to each land-cover component being selected. Table 3 shows detailed information about endmembers in the ROSIS data. Unlike HySpex data, the impervious surfaces in ROSIS data have only one component. This is because the materials of the impervious surfaces in the ROSIS data are relatively simple and are similar, so impervious surfaces are considered as one category.

### 3.4 Impervious Surface Estimation

In this paper, impervious surfaces in HySpex data consist of high albedo and low albedo and impervious surfaces in ROSIS data consist of one component, which may contain many
endmembers. Therefore, its overall fraction can be calculated by adding all the fractions of its endmember signatures. However, when some low-reflectance materials (e.g., water and shadow) and high-reflectance materials (e.g., dry soil) are mixed with impervious surfaces, they are difficult to separate, which affects impervious surface estimation. There is no water area in the study area, so its effect can be neglected. When the fractions of bare soil and shadow were obtained, the pixels with high values were masked to reduce their effects.

### 3.5 Accuracy Assessment

For HySpex data, a higher spatial resolution image with 0.25 m was used as reference which could clearly distinguish all land-cover types. To obtain the proportions of the impervious surfaces, the original image was resampled to 0.25 m and georeferenced with the high-spatial-resolution image. Then the proportions of the impervious surfaces could be obtained by visual interpretation. A total of 285 samples were randomly selected.

For ROSIS data, the simulated data were applied to validate the effectiveness of the proposed method. 140 simulated test samples were generated as

$$g(x, y) = \left[1 + \frac{N(0, 1)}{\text{SNR}}\right] \left[\sum_{j=1}^{n} r_j a_j(x, y)\right],$$

where $g(x, y)$ is the simulated mixed pixel, $r_j$ is the $j$'th endmember, $a_j(x, y)$ is the proportion of the $j$'th endmember, and $\sum_{j=1}^{n} a_j(x, y) = 1$; $n$ is the number of endmembers, $N(0, 1)$ is the Gaussian random noise with zero mean and unit variance, and SNR is the signal-to-noise ratio; SNR = 20 in the simulation.

When the endmembers were known, 140 groups $a_j(x, y)$ were acquired, which must meet the condition that $\sum_{j=1}^{n} a_j(x, y) = 1$; then 140 mixed pixels can be simulated by using Eq. (4); after that, we used all methods to unmix the simulated data and obtained the predicted fractions. The root-mean-squared error (RMSE) and $R^2$ of actual fractions and predicted fractions were calculated for accuracy assessment.

In this paper, the RMSE and the correlation coefficient ($R^2$) are used to measure the accuracy of the impervious surface estimation; they are defined as

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (I_i^f - I_i)^2}{N}},$$

$$R^2 = \frac{\sum_{i=1}^{N} (I_i^f - \bar{I})^2}{\sum_{i=1}^{N} (I_i - \bar{I})^2},$$

where $I_i^f$ is the estimated impervious surface fraction for sample $i$, $I_i$ is the impervious surface proportion derived from a 0.25-m resolution image for sample $i$, $\bar{I}$ is the mean value of the samples, and $N$ is the number of samples.

### 4 Results and Discussion

#### 4.1 HySpex Experiment

##### 4.1.1 Endmember spectra and candidate models

In SMA, an endmember spectral signature is very important because it is the foundation of the test. The nine endmembers contained in four land-cover types and shadow were obtained using the method in Sec. 3.3. To test the effectiveness of MMESMA for the high-spatial-resolution hyperspectral images, LSMA, the original MESMA, and support vector machine (SVM) were applied as well as MMESMA using the same spectral library (in Fig. 3). The model used by LSMA is to combine all endmembers corresponding to level 3 in Table 2. As explained in
Sec. 3.2, the candidate models for multiple unmixing were constructed by different land-cover components (include two or three), which are defined in Table 2.

Table 4 shows all the candidate models for MESMA and MMESMA, where H, L, V, B, and S are the codes of the land-cover components in Table 2. The number of the total candidate models for MMESMA is 10, while it is 68 for MESMA. That is, the number of tests for selecting the best-fit model for each pixel to MMESMA is much less than the original MESMA, which indicates a lower computational cost. In the HySpex experiment, the computing time of MMESMA is 5.5 times less than that of MESMA.

4.1.2 Abundance fraction images of all land-cover components and shadow

After defining the candidate models, the best-fit model for each pixel was selected using the method in Sec. 3.2. Then LSMA, the original MESMA, SVM, and MMESMA were used for unmixing.

As for SVM, the pixels that represent different classes were selected with reference to the 0.25-m image to construct the training set. There are 3641 training samples in this experiment.

Figure 4 shows the fraction images of the land-cover components and shadow as defined in Table 2. The high albedo of the impervious surfaces, the low albedo of the impervious surfaces, and the vegetation fraction were obtained by adding all endmember fractions belonging to the same land-cover component. The greater the value of the pixel, the brighter it is shown. From the visual perspective, the results of unmixing at the edge of land cover (especially the shadow fraction) are better than that of the internal area land cover when using MESMA [see Fig. 4(b)]. The results of unmixing by using LSMA and MMESMA are better than those of MESMA. These confirm that MESMA accounts for the mixtures between different land-cover types and may overlook the mixture between different objects within the same land-cover type.
4.1.3 Impervious surface and accuracy

As explained in Sec. 3.4, when the fractions of all land-cover components and shadow were obtained, the overall fractions in the five level 2 classes were calculated and displayed in Fig. 5. The accuracy of impervious surfaces was evaluated using the methods in Sec. 3.5.

Table 5 shows that the RMSE of the result for LSMA is 33.83%, that for MESMA is 40.09%, that for MMESMA is 11.71%, and that for SVM is 22.41%. The correlation coefficient ($R^2$) is 0.5893 for LSMA, 0.5200 for MESMA, 0.9656 for MMESMA, and 0.8850 for SVM. That is to say, both the RMSE and $R^2$ indicate that MMESMA is better for unmixing high-spatial-resolution images than LSMA, the original MESMA, and SVM. Figure 6 shows the scatter plots of the accuracy assessment results, which fully bear out the superiority of MMESMA again.

Compared to LSMA, the advantage of MMESMA is to allow the numbers and types of endmembers for unmixing to vary on a per-pixel basis, which reduces the error produced by the phenomenon such that the endmembers for unmixing are more than the actual number of endmembers. For a high-spatial-resolution image, the mixture between different land-cover types is few and there are a great deal of mixtures between objects belonging to the same land-cover type, because of the spectral variation inherent in the same land cover. The superiority of MMESMA is such that when the candidate models are constructed, both the mixture between different land-cover types and the mixture between different objects within the same land-cover type are accounted for. Its performance is even better than the nonlinear SVM.

Table 4 All candidate models for multiple endmember spectral mixture analysis (MESMA) and modified MESMA (MMESMA).

<table>
<thead>
<tr>
<th>Number of land-cover classes</th>
<th>All candidate models in terms of classes</th>
<th>Number of candidate models in MMESMA</th>
<th>Number of candidate models in MESMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>H + L + S</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>H + V + S</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>H + B + S</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>L + V + S</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>L + B + S</td>
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</tr>
<tr>
<td></td>
<td>V + B + S</td>
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<td>3</td>
</tr>
<tr>
<td>3</td>
<td>H + L + V + S</td>
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<tr>
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<td></td>
<td>H + V + B + S</td>
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<td>6</td>
</tr>
<tr>
<td></td>
<td>L + V + B + S</td>
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<td>9</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>10</td>
<td>68</td>
</tr>
</tbody>
</table>

Table 5 Comparison in accuracy of estimated fractions for impervious surfaces.

<table>
<thead>
<tr>
<th>Methods</th>
<th>LSMA</th>
<th>MESMA</th>
<th>MMESMA</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>33.83%</td>
<td>40.09%</td>
<td>13.20%</td>
<td>22.41%</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.5893</td>
<td>0.5200</td>
<td>0.9656</td>
<td>0.8850</td>
</tr>
</tbody>
</table>

Note: LSMA, linear spectral mixture analysis; SVM, support vector machine; RMSE, root-mean-squared error.
Fig. 4 Abundance fraction images by using (a) linear spectral mixture analysis (LSMA), (b) multiple endmember spectral mixture analysis (MESMA), (c) modified MESMA (MMESMA), and (d) support vector machine (SVM). From left to right: impervious high, impervious low, vegetation, bare soil, shadow.
4.2 ROSIS Experiment

The same methods were applied to ROSIS data as well as to HySpex data. As for SVM, there are 2592 samples in the training set. 140 validation samples are simulated by using the method in Sec. 3.5 as well as using other methods. Figure 7 shows the selected eight endmembers in the ROSIS data, which correspond to the endmember class in Table 3. The candidate models for MESMA and MMESMA are shown in Table 6, where I, L, V, B, and S are the codes of the land-cover components in Table 3. The number of the total candidate models for MMESMA is 4.

![Fig. 5](image1.png) Impervious surface fractions by using LSMA, MESMA, MMESMA, and SVM.

![Fig. 6](image2.png) Accuracy assessment of estimated fractions for impervious surface by using different methods: (a) LSMA, (b) MESMA, (c) MMESMA, and (d) SVM.
Fig. 7 Normalized spectral reflectance for different endmember classes; the electromagnetic radiation in the spectral range between 414 and 2512 nm, which was represented by index number between 1 and 103 (the number of total bands).

Table 6 All candidate models for MESMA and MMESMA.

<table>
<thead>
<tr>
<th>Number of land-cover classes</th>
<th>All candidate models in terms of classes</th>
<th>Number of candidate models in MMESMA</th>
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</tr>
</thead>
<tbody>
<tr>
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<td>I + V + S</td>
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<tr>
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<td>I + B + S</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>V + B + S</td>
<td></td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>I + V + B + S</td>
<td></td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Total</td>
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<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>24</td>
</tr>
</tbody>
</table>

Fig. 8 Impervious surface fractions by using LSMA, MESMA, MMESMA, and SVM.
while it is 24 for MESMA. In the ROSIS experiment, the computing time of MMESMA is six times less than MESMA. Figure 8 shows the impervious surface fractions using LSMA, MESMA, MMESMA, and SVM.

By using the method in Sec. 3.5, 140 simulated test samples were applied to validate the accuracy of estimated fractions for impervious surfaces; the results are shown in Table 7 and Fig. 9. Table 7 shows that the RMSE of the result is 56.15% for LSMA, 56.20% for MESMA, 4.51% for MMESMA, and 18.30% for SVM. The correlation coefficient ($R^2$) is 0.51 for LSMA, 0.03 for MESMA, 0.98 for MMESMA, and 0.86 for SVM. These demonstrate that the proposed MMESMA can generate more reliable abundance fractions for ROSIS data. The scatter plots of the accuracy assessment results shown in Fig. 9 fully illustrate that MMESMA is better for unmixing high-resolution hyperspectral imagery than LSMA, the original MESMA, and SVM.

## 5 Conclusion

Classification methods were often applied to impervious surface mapping from coarse- and medium-resolution multispectral images. Few papers were published on spectral unmixing for impervious surface mapping using high-spatial-resolution hyperspectral image. The classical

<table>
<thead>
<tr>
<th>Methods</th>
<th>LSMA</th>
<th>MESMA</th>
<th>MMESMA</th>
<th>SVM</th>
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<tr>
<td>RMSE</td>
<td>56.15%</td>
<td>56.20%</td>
<td>4.51%</td>
<td>18.30%</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.51</td>
<td>0.03</td>
<td>0.98</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Fig. 9 Accuracy assessment of estimated fractions for impervious surface by using different methods: (a) LSMA, (b) MESMA, (c) MMESMA, and (d) SVM.
spectral unmixing decomposes the mixtures between different land-cover types using the same set of endmembers. In this paper, a method of multiple endmember unmixing for high-spatial-resolution hyperspectral images, i.e., MMESMA, was proposed by extending the original MESMA. The mixtures decomposed by MMESMA were not only from different land-cover types, but also from different signatures within the same land-cover type. Therefore, this method can handle the variability in the same land-cover type in high-spatial-resolution hyperspectral images. Experimental results demonstrate that MMESMA outperforms other popular methods, such as LSMA, MESMA, and SVM.

Acknowledgments
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References

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