Vectorial boundary-based sub-pixel mapping method for remote-sensing imagery

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This article presents a vectorial boundary-based sub-pixel mapping (VBSPM) method to obtain the land-cover distribution with finer spatial resolution in mixed pixels. With inheritance from the geometric SPM (GSPM), VBSPM first geometrically partitions a mixed pixel using polygons, and then utilizes a vectorial boundary extraction model (VBEM), rather than the rasterization method in GSPM, to determine the location and length of each edge in the polygon, while these edges are located at the boundary of and within the interior of the mixed pixel. Furthermore, VBSPM uses a decay function to manage the mixed pixels along the image boundary region due to the missing parts of their neighbours. Finally, a ray-crossing algorithm is employed to determine the land-cover class of each sub-pixel in terms of vectorial boundaries. The experiments with artificial and remotely sensed images have demonstrated that VBSPM can reduce the inconsistency between the boundaries of different land-cover classes, approximately calculating errors with an odd zoom factor, and achieve more accurate sub-pixel mapping results than the hard classification methods and GSPM.

1. Introduction

Sub-pixel mapping (SPM) is a technique used to transform fraction images obtained from soft classification into a hard classification map, the spatial resolution of which is finer than the originally input remotely sensed imagery (Atkinson 1997, 2009). Most commonly, SPM methods have been developed under the assumptions of spatial dependence both within and between image pixels. Tatem et al. (2001) used the Hopfield neural network to indicate the distribution of sub-pixels. Boucher and Kyriakidis (2006) presented a method with indicator geostatistics. Mertens et al. (2006) utilized a sub-pixel/pixel spatial attraction model to identify the location of sub-pixels. Zhang et al. (2008) proposed an approach based on a BP neural network. Ardila et al. (2011) adopted a Markov random field to obtain the arrangement of sub-pixels. Ling et al. (2012) introduced an object-based method. Zhong and Zhang (2012) employed the adaptive differential evolution to achieve the configuration of sub-pixels. These methods can be classified into two categories: regression-type and spatial optimization-type (Atkinson 2009). The first category is fast and provides information on uncertainty but requires auxiliary data for regression excluding the spatial attraction model (Mertens et al. 2006; Wang et al. 2013); the second category approximately accounts for support in the prediction process but involves iterations in a time-consuming procedure. Recently, Ge

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et al. (2009) developed a method, named the geometric SPM (GSPM), which utilizes polygons to represent the spatial location of land-cover classes within a mixed pixel. Based on the assumption of spatial dependence, the locations of the vertices of polygons might be calculated and determined according to the proportions of the land-cover classes in the mixed pixel and its neighbouring ones. Compared with the previous two categories of methods, GSPM performs the calculation without iterative operations, and its implementation relies upon the area proportions within mixed pixels and does not require auxiliary data (Ge et al. 2009). As a follow-up study, GSPM was enhanced to produce finer land-cover maps by leveraging with the multiple-point simulation (Ge 2013).

GSPM is considered an advanced SPM method capable of providing details on spatial distribution of land-cover classes within a mixed pixel (Zhong and Zhang 2012); it has still, however, issues to improve. (1) The zoom factor of an odd number would introduce more rounding error when determining the locations of the vertices of polygons within the mixed pixel. (2) For the case of multiple land-cover classes existing within a mixed pixel, the boundaries of different land-cover classes generated with the GSPM may be inconsistent. Although the method allows for fine-tuning between the spatial distributions of different land covers to obtain as consistent as possible a boundary, the fine-tuning might affect the output accuracy. In addition, SPM methods that are under the assumption of spatial dependence commonly suffer from the issue of missing parts of neighbours in the boundary region; e.g. the BP-based method (Zhang et al. 2008) and GSPM (Ge et al. 2009). This means the final output sub-pixel image might not contain the region indicated by the edge pixels (Zhong and Zhang 2012). However, it should be noted that a sub-pixel/pixel spatial attraction model with the assumption of spatial dependence (Mertens et al. 2006; Wang et al. 2013) can be performed with the limited neighbours when dealing with the edge pixels.

Handling the aforementioned shortcomings of GSPM, this article proposes a vectorial boundary-based sub-pixel mapping method (VBSPM) that follows the GSPM idea to geometrically partition a mixed pixel using polygons and further bring forward a vectorial boundary extraction model to decrease the rounding error and inconsistency between the boundaries of different land-cover classes. For the unclassified regions along the border of the original remotely sensed imagery, VBSPM utilizes a decay function (Ge et al. 2005) to obtain the supplementary boundary information for these mixed pixels to predict the distributions of sub-pixels. Both artificial and remotely sensed images are used to evaluate the performance of the VBSPM method.

2. VBSPM

Given one mixed pixel \( P_m \), named as the central pixel, and its neighbouring pixels \( P_i (i = 0, 1, ..., 7) \) as described in Figure 1, \( P_m \) has four vertices C, F, I, and L, and its whole boundary is equally divided into eight segments, AB, BCD, DE, EFG, GH, HIJ, JK, and KLA (Ge et al. 2009). It assumes that each neighbouring pixel corresponds to one of eight boundary segments of the central mixed pixel, i.e. the proportions of land-cover classes in the neighbouring pixel determine the land-cover distribution mapping on the boundary segment. The distribution in the central pixel is mapped to two mutually perpendicular line segments MN and PQ at the centre O, and their lengths are equal to that of AB. In GSPM, the zoom factor is used as a precedent condition and the mixed pixels are rasterized by the given zoom factor. Subsequently, the boundaries of the mixed pixel are then obtained with the GSPM method. Correspondingly, the classes of sub-pixels within a mixed pixel can be known using the GSPM method, which is a method based on the raster data structure.
To resolve the inherent issues hidden in GSPM, VBSPM redesigns the strategy of generating detailed land-cover maps at the sub-pixel scale. It proposes a dedicated vectorial boundary extraction model (VBEM) to manage the aforementioned rounding error and inconsistency. Unlike GSPM, VBSPM is a method based on vector data structure. It first estimates the locations of all polygons within the mixed pixel and then sets the zoom factor. Third, with the given zoom factor, the attribute of each sub-pixel within the mixed pixel is determined by the ray-crossing method (Gomboši and Žalik 2005). Last, a decay function is employed to deal with the boundary region of the image.

2.1. Estimating locations of polygons with the VBEM

VBEM is proposed as a vector-oriented approach to extract information on edges, i.e. size and location, of the polygon that is used to map the spatial distribution of land-cover classes in the mixed pixel. VBEM does not require the zoom factor and can determine all polygons within the mixed pixel in two steps.

The operational principle of the VBEM is outlined in Figure 2. Assume that there are two land-cover types – land-cover classes C_1 and C_2 – within a region covered by 3 pixels × 3 pixels. The proportions of classes C_1 and C_2 for the central pixel P_m and its neighbouring pixels P_i are P_m{0.7, 0.3}, P_0{0.35, 0.65}, P_1{0.95, 0.05}, P_2{1, 0}, P_3{1, 0}, P_4{1, 0}, P_5{0.65, 0.35}, P_6{0, 1}, and P_7{0, 1}, respectively, as shown in Figure 2(a).

**Step 1: Estimate the length and location of each segment.** The length and location of each segment for all classes in the mixed pixel are estimated as

\[
L_{ijk} = S_{ik},
\]

\[
V_{ijk} = V_{ijk}^{(0)} + \begin{cases} 
(1 - S_{ik}) \frac{S_{(i+1)k} - S_{(i-1)k}}{S_{(i+1)k} + S_{(i-1)k}} & S_{(i+1)k} \neq S_{(i-1)k} \\
(1 - S_{ik}) \frac{1}{2} & \text{otherwise}
\end{cases},
\]

where \(L_{ijk}\) denotes the length of segment \(j\) (\(j = \text{AB}, \text{BCD}, \ldots, \text{KLA}, \text{MN}, \text{PQ}\)) corresponding to the pixel \(i\) (\(i = 0, 1, \ldots, 7\)) for class \(k\) (\(k = 1, 2, \ldots, K\)); \(S_{ik}\) denotes the proportion of...
class \( k \) in the pixel \( i \); \( S_{i+1}^k \) and \( S_{i-1}^k \) denote the proportions of class \( k \) to the left and right of pixel \( i \), respectively; \( V_{ijk} \) indicates the initial location of the start point on segment \( j \) corresponding to pixel \( i \) of class \( k \), which starts at the left vertex of its segment, while \( V_{ijk} \) denotes the final location of the start point by shifting a segment calculated with \( S_{i+1}^k \) and \( S_{i-1}^k \) as shown in Equation (2). It is seen that the zoom factor does not appear in the equations. Therefore, compared with GSPM, the new equations eliminate rounding errors resulting from the zoom factor, especially the odd one.

An example for calculating the length and location of edges in the polygon representing the land-cover class \( C_1 \) in the central pixel is shown in Figure 2(b). The polygon edge on the segment \( AB \) is \( V_1V_2 \), which is calculated as \( |V_1V_2| = P_{01}|AB| = 0.35|AB| \), where \( P_{01} \) is the proportion of class \( C_1 \) in its neighboring pixel \( P_0 \) as mentioned in the above testing example region of 3 pixels × 3 pixels; the edge on the polyline \( BCD \) is \( V_3CV_4 \), and \( |V_3CV_4| = 0.95|BCD| \); and so on. Particularly, the polygon vertices within the central pixel are determined by the line segments \( T_1T_3 \) and \( T_4T_2 \), where \( |T_1T_3| = 0.7|PQ| \) and \( |T_4T_2| = 0.7|MN| \).

**Step 2: Obtain the polygon for the land-cover class.** The initial polygon is generated by connecting the vertices determined in Step 1 in the counterclockwise direction, as shown by the dotted lines in Figure 2(b). It is noteworthy that a supplemental connecting rule requires that the vertices on \( PQ \) and \( MN \) should be passed through explicitly. For instance, the initial polygon vertices of the land-cover class \( C_1 \) are \( V_2, T_1, V_3, C, V_4, T_2, V_5, V_6, V_7, F, V_8, T_3, V_9, V_{10}, T_3, V_{11}, V_{12}, T_4, T_1, \) and \( V_1 \), where the vertices of \( T_1, T_2, T_3, \) and \( T_4 \) are inside the mixed pixel. Particularly, some vertices are coincident with each other, such as \( B \) coincides with \( V_2; D \) coincides with \( V_4 \) and \( V_5); \) \( M \) coincides with \( T_2; \) and so on. It is seen that several pairs of segments connecting these interior vertices are almost coincident, and just there exists an extremely small angle between each pair of the line segments, such as \( V_2T_1 \) and \( T_1V_3 \), forming small gaps in the polygon. Therefore, it is necessary to determine an appropriate way to manage these gaps. We take two cases into account.

**Case 1:** If the angle between the two vectors \( V_jT_i \) and \( T_iV_{j+1} \) is less than a predefined threshold value \( \theta \) and the vertices \( V_j \) and \( V_{j+1} \) are not on the same line segment, then vertex \( T_i \) will be deleted. This can be expressed as follows:
delete \( (T_i) \), if \( \cos^{-1} \left( \frac{\left[ V_j T_i \cdot [T_i V_{j+1}] \right]}{|V_j T_i \times |T_i V_{j+1}||} \right) \leq \theta \) and \( V_j, V_{j+1} \) not on the same segment.

where \( T_i \) is a vertex within the pixel; \( V_j, V_{j+1} \) are the two neighbouring vertices of \( T_i \); and \( \theta \) is the threshold. Based on extensive experimental results, the applicable threshold is set to \( 5^\circ \).

**Case 2:** If the angle described in case 1 is less than the threshold value and the two vertices are on the same segment, \( V_j \) and \( V_{j+1} \) will be deleted. This can be expressed as follows:

\[
delete (V_j, V_{j+1}), \text{ if } \cos^{-1} \left( \frac{\left[ V_j T_i \cdot [T_i V_{j+1}] \right]}{|V_j T_i \times |T_i V_{j+1}||} \right) \leq \theta \text{ and } V_j, V_{j+1} \text{ on the same segment.}
\]

After the processing, some vertices of the initial polygon will be deleted. In Figure 2(b), the vertices of \( T_2 \) and \( T_3 \) are deleted. The final polygons are then sequentially connected with these numbered vertices \( (V_i) \), as shown in Figure 2(c).

### 2.2. Determining the attribute value of sub-pixels

As VBEM is based on a vector data structure, the land-cover labels for sub-pixels need to be assigned after the polygons within the mixed pixel are obtained and the zoom factor is set. This article uses the ‘ray-crossing’ method (Gomboši and Žalik 2005) to determine the attribute value of sub-pixels. From the central point of the sub-pixel, a ray in any direction can be drawn and then the number of intersections with the edges of one polygon can be counted. If the number is odd, it means the central point is inside the polygon and then the sub-pixel is assigned with the land-cover label that the polygon corresponds to. Otherwise the central point is outside the polygon and then we repeat the process for the remaining polygons until its attribute is determined.

### 2.3. Handling the boundary region with a decay function

To manage mixed pixels along the boundary region of remotely sensed imagery, a decay function is introduced to enhance the ability. Using a linear, exponential, or hyperbolic growth model (Ge et al. 2005), the decay function is an effective way to obtain values on eight neighbouring pixels of the mixed pixel located in the boundary region, and it is able to feed the supplementary boundary information into the spatial dependence-based sub-pixel mapping methods. In this article, a linear decay function is used to fill values of pixels that are the neighbouring pixels of the edge pixels outside the fraction image and thus avoid leading to unclassified regions along the border of input remotely sensed imagery (Zhong and Zhang 2012).

### 3. Experiments

In the experiments, we use one artificial image and two remote-sensing images to compare the performance of VBSPM and GSPM. Each of the algorithms programmed in C++ is executed on the 32-bit Windows 7 operating system. The experimental setup is an Intel Core2 E7500 2.93GHz processor and 4 GB memory.
3.1. Artificial imagery

A simulated land-cover image was created to validate the performance of the proposed method. The simulated image is 630 pixels × 630 pixels, containing five classes, named C1, C2, C3, C4, and C5, as shown in Figure 3(a). It is used as the reference image (RI) to assess the accuracy of SPM results acquired by GSPM and VBSPM. The simulated image is degraded by a mean filter with degraded factors of 5, 7, 9, and 15 to obtain the proportions of each class in each mixed pixel with lower resolution. The fraction images are hardened into hard classification results as shown in Figure 3(b). In this experiment, only the mixed pixels in the degraded fraction images are processed to achieve the spatial distribution of sub-pixels while the pure pixels are directly divided into sub-pixels by assigning the same label. To facilitate comparison and analysis, the zoom factors to GSPM and VBSPM are also set to 5, 7, 9, and 15. Both methods generate the sub-pixel mapping results with the zoom factors of 5, 7, 9, and 15. Figures 3(c) and (d) present the results.
from GSPM and VBSPM, respectively, and the accuracy assessments for SPM results are given in Table 1. With the zoom factors of 5, 7, 9 and 15, the computation times of GSPM and VBSPM are 0.41s and 1.021s, 0.393s and 1.526s, 0.379s and 2.245s, and 0.399s and 4.44s, respectively. Owing to the process of determining the attribute values of sub-pixels, VBSPM needs more time to obtain the results. The difference images (DI) between the RI and the output images generated by GSPM and VBSPM are shown in Figures 3(e) and (f), respectively.

3.2. Landsat 5 TM imagery

A Landsat 5 TM imagery was used in this section with a spatial resolution of 30m, acquired on 30 August 2009. The image size is 400 pixels × 400 pixels. Its upper left latitude and longitude coordinates are 117° 03’ 36” E and 36° 04’ 26” N, and its lower right latitude and longitude coordinates are 117° 51’ 34” E and 36° 37’ 55” N, respectively. Figure 4(a) shows its pseudocolour composition image of bands 2, 3, and 4. The reference image covering the same area and taken on the same date was obtained from DigitalGlobe with the re-sampled spatial resolution of 6 m, as shown in Figure 4(b). Five land-cover classes – bare ground, buildings, roads, vegetation, and water – are evident within the high-resolution reference image and considered as endmembers for classification, sub-pixel mapping, and validation. The representative pixels of each endmember, generated by manually selecting from the image scene, are used for classification. The total number of endmembers is 2500 pixels, including 280 pixels of bare ground, 514 pixels of buildings, 146 pixels of roads, 1465 pixels of vegetation, and 95 pixels of water.

To compare the performances of the proposed method and GSPM, one hard classification named the maximum likelihood classifier (MLC) is involved in the experiments. Commonly, SPM takes the outputs of soft classification as its input to predict the spatial locations of different land-cover classes within each pixel (Ge 2013). In this experiment, the Bayesian soft classifier was employed to obtain the fraction images. Figure 4(c) presents the MLC result and land-cover maps with finer spatial resolution derived from GSPM and VBSPM with a zoom factor of 5 as shown in Figures 4(d) and (e). The computation times for GSPM and VBSPM are 12.768 s and 22.665 s, respectively. These two finer land-cover maps are 2000 pixels × 2000 pixels with a spatial resolution of 6 m. To assess the accuracy of the results, a random sampling scheme was used to select 2500 validation points as test data from Figure 4(b) according to the prior knowledge of this study area. The 2500 validation points are first visually interpreted into land-cover classes.

<table>
<thead>
<tr>
<th>Overall accuracy (%)</th>
<th>Zoom factor</th>
<th>GSPM</th>
<th>VBSPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excluding pure pixels</td>
<td>5</td>
<td>82.29</td>
<td>87.78</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>82.17</td>
<td>87.41</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>81.24</td>
<td>86.41</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>77.88</td>
<td>83.01</td>
</tr>
<tr>
<td>Including pure pixels</td>
<td>5</td>
<td>95.65</td>
<td>97.09</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>93.14</td>
<td>95.40</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>90.65</td>
<td>93.61</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>82.63</td>
<td>87.90</td>
</tr>
</tbody>
</table>

Table 1. Accuracy with the artificial imagery.
according to the high spatial resolution reference image and then they are used for quantitative accuracy assessment by comparing with the corresponding points in the results of hard classification and the two SPM methods. A confusion matrix (Tso and Mather 2001) was used to extract the producer’s accuracy, user’s accuracy, overall accuracy, and kappa coefficient and to quantitatively evaluate the accuracy of MLC, GSPM, and VBSPM results. Table 2 presents the accuracy assessments.

Table 2. Accuracy of hard classification and SPM with Landsat 5 TM imagery.

<table>
<thead>
<tr>
<th>Method</th>
<th>BG</th>
<th>BD</th>
<th>RD</th>
<th>VG</th>
<th>WT</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLC</td>
<td>UA (%)</td>
<td>53.45</td>
<td>77.15</td>
<td>29.32</td>
<td>91.71</td>
</tr>
<tr>
<td></td>
<td>PA (%)</td>
<td>57.50</td>
<td>76.85</td>
<td>65.07</td>
<td>80.82</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy (%) = 76.24 kappa coefficient = 0.6247</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GSPM</td>
<td>UA (%)</td>
<td>75.21</td>
<td>78.07</td>
<td>35.34</td>
<td>92.51</td>
</tr>
<tr>
<td></td>
<td>PA (%)</td>
<td>62.86</td>
<td>81.71</td>
<td>68.49</td>
<td>86.83</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy (%) = 81.52 kappa coefficient = 0.6997</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VBSPM</td>
<td>UA (%)</td>
<td>70.01</td>
<td>84.62</td>
<td>42.31</td>
<td>96.45</td>
</tr>
<tr>
<td></td>
<td>PA (%)</td>
<td>73.57</td>
<td>79.18</td>
<td>75.34</td>
<td>90.92</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy (%) = 85.28 kappa coefficient = 0.7611</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: BG, bare ground; BD, building; RD, road; VG, vegetation; WT, water; UA, user’s accuracy; PA, producer’s accuracy.
3.3. ZY-3 imagery

To further investigate the proposed method, another case study is carried out using ZY-3 imagery. Details about ZY-3 satellite and images can be found on the following website: http://sjfw.sasmac.cn/en.html. The image size is 200 pixels × 200 pixels and its spatial resolution is 5.8 m, as shown in Figure 5(a). Its upper left latitude and longitude coordinates are 116° 04’ 18” E and 40° 05’ 49” N, and its lower right latitude and longitude coordinates are 116° 14’ 53” E and 40° 14’ 56” N, respectively. The reference image covering the same area was obtained from DigitalGlobe with a re-sampled spatial resolution of 1.16 m, as shown in Figure 5(b). This area mainly includes five classes of land cover, namely water, grass, tree, buildings, and bare ground. Representative pixels for classification, sub-pixel mapping, and validation are manually selected from Figure 5(a). The total number of endmembers is 767 pixels, including 195 pixels of water, 139 pixels of grass, 184 pixels of tree, 165 pixels of buildings, and 84 pixels of bare ground.

Similarly to the above experiment, GSPM and MLC hard classification methods are also involved in the experiments and the Bayesian soft classifier was employed to obtain the fraction images. In this experiment, the zoom factor is set to 5. Results from MLC, GSPM, and VBSPM are presented in Figures 5(c)–(e), respectively. The computation times for GSPM and VBSPM are 3.049 s and 12.306 s, respectively. A random sampling scheme was also used to select 2600 validation points from Figure 5(b) for quantitative accuracy assessment. Table 3 illustrates its accuracy assessments with the producer’s accuracy, user’s accuracy, overall accuracy, and kappa coefficient.

Figure 5. Experiment with ZY-3 imagery. (a) ZY-3 imagery acquired on 17 April 2012; (b) validation data of DigitalGlobe imagery acquired on 4 October 2011; (c) MLC result; (d) GSPM result; (e) VBSPM result; (f) MLC, GSPM, and VBSPM results of the magnified area marked by the yellow rectangle at the bottom of (a).
4. Discussion

4.1. Accuracy assessment

The accuracy measures of the artificial image listed in Table 1 show that both methods produce the SPM results with high precision when the image is concerned as a whole. In the case of only counting the mixed pixels in the image, the overall accuracies of VBSPM are 5.49%, 5.61%, 5.17%, and 5.13% higher than GSPM. In particular, the SPM result of VBSPM incorporating VBEM with the zoom factor of 5 has obtained around 87.78% of the overall accuracy for mixed pixel accuracy statistics. With the changes of zoom factors, the proportions of mixed pixels are 23.79%, 36.54%, 64.03%, and 71.20%, respectively. It can be found from Table 1 that if mixed pixels in an image take a small proportion, the overall accuracy (including pure pixels) from VBSPM improves slightly. However, it gradually increases as the proportions of mixed pixels become larger. The results demonstrate that the VBEM model can depict more accurate spatial distribution of land-cover classes within mixed pixels using the vector-oriented data structure instead of the raster structure in GSPM. Especially, the rounding errors can be reduced in calculating the locations of the vertices of polygons by the vector-oriented boundaries.

Table 2 lists the accuracy assessments of the MLC, GSPM, and VBSPM results with a zoom factor of 5 for Landsat 5 TM imagery. It implies that the accuracy of the two SPM results is better than that of the traditional hard classification. The better performance of the SPM methods relates to the generation of more accurate and detailed land-cover maps at sub-pixel scales. Meanwhile, the VBSPM can produce the most accurate classification result among the three methods. Compared with GSPM, the PAs of bare ground, road, vegetation, and water increase around 11%, 7%, 4%, and 8%, respectively. The overall accuracy of VBSPM is around 9% and 5% higher than that of MLC and GSPM, respectively, and its kappa coefficient reaches 0.7611. In addition, the produce’s accuracy for roads is nearly 7% better than GSPM, which demonstrates the feasibility of applying the VBSPM to mapping some linear features.

Table 3. Accuracy of hard classification and SPM with a ZY-3 imagery.

<table>
<thead>
<tr>
<th>Method</th>
<th>WT</th>
<th>GS</th>
<th>TR</th>
<th>BD</th>
<th>BG</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLC</td>
<td>UA (%)</td>
<td>97.45</td>
<td>81.02</td>
<td>73.47</td>
<td>76.35</td>
</tr>
<tr>
<td></td>
<td>PA (%)</td>
<td>89.96</td>
<td>89.69</td>
<td>72.26</td>
<td>67.25</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy (%) = 76.54 kappa coefficient = 0.7055</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GSPM</td>
<td>UA (%)</td>
<td>95.28</td>
<td>80.91</td>
<td>86.22</td>
<td>79.19</td>
</tr>
<tr>
<td></td>
<td>PA (%)</td>
<td>90.60</td>
<td>89.88</td>
<td>79.93</td>
<td>76.79</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy (%) = 81.96 kappa coefficient = 0.7738</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VBSPM</td>
<td>UA (%)</td>
<td>97.12</td>
<td>92.66</td>
<td>92.38</td>
<td>79.71</td>
</tr>
<tr>
<td></td>
<td>PA (%)</td>
<td>93.59</td>
<td>93.39</td>
<td>86.31</td>
<td>82.65</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy (%) = 87.31 kappa coefficient = 0.8409</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: WT, water; GS, grass; TR, tree; BD, building; BG, bare ground.

The accuracy statistics of the MLC, GSPM, and VBSPM results with a zoom factor of 5 for ZY-3 imagery are displayed in Table 3. It shows that the accuracies of the two SPM results are higher than that of the hard classification MLC. In addition, the overall accuracy of VBSPM is around 11% and 6% higher than the results from MLC and GSPM, respectively, and its kappa coefficient reaches 0.8409. Compared to GSPM, the PA of VBSPM for each land-cover class has higher values. They are all over 81% and the
highest PA of water reaches 93.59%. For example, the PAs for water and grass improve over 3%, and the tree and building improve around 6%. The PA for bare ground improves over 7%. The additional experiment further demonstrated the feasibility of VBSPM.

4.2. Enhancements on the classified image quality

Simulation fidelity: Figures 3(e) and (f) display the difference images between SPM results (GSPM and VBSPM) and reference image. In the difference images, it can be found that VBSPM has better quality than GSPM, especially around the boundary regions. Figures 4(f) and (g) show two magnified areas of the sub-pixel mapping results in Landsat TM 5 imagery; they are used to compare the image quality between GSPM and VBSPM results. The (i) parts of Figures 4(f) and (g) are the TM images of two magnified areas. (ii) and (iii) of Figure 4(f) show the first magnified area results of GSPM and VBSPM, respectively. (ii) and (iii) of Figure 4(g) show the second magnified area results of GSPM and VBSPM, respectively. (i), (ii), and (iii) of Figure 5(f) are the MLC, GSPM, and VBSPM results, which are in the magnified area marked by the yellow rectangle in Figure 5(a) for ZY-3 imagery. It can be found that two SPM methods provide smoother boundaries and more detailed land-cover maps than hard classification. The VBSPM result is closer to reality than the GSPM result and it can effectively eliminate some system noise caused by rounding errors and inconsistency between different boundaries of land-cover classes.

Boundary region: The GSPM result as shown in Figure 3(b) shows that it lacks the sub-pixel distributions on its boundary expressed in black. The VBSPM result in Figure 3(c) is able to indicate the sub-pixel distribution on the boundary of the SPM map, which is because the VBSPM utilizes the linear decay function to complete the eight-neighbour pixel information for these edge pixels on the boundary to predict the distributions of sub-pixels. (iii) of Figure 4(g) and (iii) of Figure 5(f) show that VBSPM can also handle the edge pixels to obtain its distributions of sub-pixels for Landsat TM 5 imagery and ZY-3 imagery, whereas GSPM does not manage it, expressing in black on the right and bottom of (ii) in Figure 4(g) and (iii) in Figure 5(f).

4.3. Source of errors

Regarding the issue of fraction error in the proposed algorithm, it is similar to GSPM, which suffers from the error inherent within the data after soft classification (Ge et al. 2009). In the TM imagery experiment, owing to the spectral similarity of road and bare ground, it leads to the difficulty of distinguishing roads from bare ground. As a result, the fraction errors are inevitably propagated into the SPM results and then lower their accuracies. Similarly, in the ZY-3 imagery experiment the spectrum difference between buildings and bare ground is not obvious. Therefore, fraction errors in these two classes might lead to the low accuracies as displayed in Table 3. However, Ge (2013) proposed a solution by leveraging with the multiple-point simulation to reduce the error. Although there is little inevitable fraction error from soft classification, an artificial image free of fraction error is used to evaluate the performance of the proposed method and the results have demonstrated its effectiveness.

In summary, according to the three experiments, it is demonstrated that the two SPM methods considered here can provide more accurate land-cover maps than the hard classification of the MLC, and VBSPM has a clear improvement of system noise in.
GSPM and can handle the edge pixels on the image boundary to obtain better sub-pixel mapping results.

5. Conclusions
GSPM was improved with a VBEM and redesigned mapping strategy. The VBEM is a vector-oriented model; therefore, VBSPM can determine all polygons within the mixed pixel without the zoom factor and reduce rounding errors in calculating boundaries of land-cover classes and inconsistency in assigning attributes to sub-pixels relative to the GSPM. However, it leads to a slightly longer computing time in VBSM than in GSPM. Three experiments demonstrate that the VBSPM can produce higher accuracy and better image quality of SPM results than GSPM, and the running time of VBSPM is merely several seconds for these two large-sized actual images. Therefore, VBSPM will be one of the efficient methods to obtain high-quality finer land-cover maps. However, VBSPM is more applicable to the high-resolution (H-resolution) case (Atkinson 2009), which is similar to GSPM. Future research efforts will emphasize dealing with the low-resolution (L-resolution) case in actual satellite imagery.

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References

