

# Unsupervised Object-based Spectral Unmixing for Subpixel Mapping

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*Abstract:* Subpixel mapping (SPM) addresses the widespread mixed pixel problem in remote sensing images by predicting the spatial distribution of land cover *within* mixed pixels. However, conventional pixel-based spectral unmixing, a key pre-processing step for SPM, neglects valuable spatial contextual information and struggles with spectral variability, ultimately undermining SPM accuracy. Additionally, while extensively utilized, supervised spectral unmixing is labor-intensive and user-unfriendly. To address these issues, this paper proposes a fully automatic, unsupervised object-based SPM (UO-SPM) model that exploits object-scale information to reduce spectral unmixing errors and subsequently enhance SPM. Given that mixed pixels are typically located at the edges of objects (i.e., the inner part of objects is characterized by pure pixels), segmentation and morphological erosion are employed to identify pure pixels within objects and mixed pixels at the edges. More accurate endmembers are extracted from the identified pure pixels for the secondary spectral unmixing of the remaining mixed pixels. Experimental results on 10 study sites demonstrate that the proposed unsupervised object (UO)-based analysis is an effective model for enhancing both spectral unmixing and SPM. Specifically, the spectral unmixing results of UO show an average increase of 3.65% and 1.09% in correlation coefficient ( $R$ ) compared to Fuzzy- $C$  means (FCM) and linear spectral mixture model (LSMM)-derived coarse proportions, respectively. Moreover, the UO-derived results of four SPM methods (i.e., Hopfield neural

network (HNN), Markov random field (MRF), pixel swapping (PSA) and radial basis function interpolation (RBF)) exhibit an average increase of 5.89% and 3.04% in overall accuracy (OA) across the four SPM methods and 10 study sites compared to the FCM and LSMM-based results, respectively. Moreover, the proportions of both mixed and pure pixels are more accurately predicted. The advantage of UO-SPM is more evident when the size of land cover objects is larger, benefiting from more accurate identification of objects.

*Keywords:* Mixed pixel, subpixel mapping (SPM), super resolution mapping, downscaling, spectral unmixing.

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## 33 **1. Introduction**

34 Land cover mapping is crucial for environmental and land management, supporting various fields such as  
35 resource management, urban planning (Wang et al., 2018; Shi et al., 2022), disaster management (Shaw and  
36 Banba, 2017), carbon sequestration monitoring (Houghton et al., 2012; Holmberg et al., 2023) and climate  
37 modeling (Pielke Sr et al., 2011). Remote sensing is adopted widely for land cover mapping, due to the  
38 common advantages of raster image format, large synoptic coverage, internal precision of measurement and  
39 repeat visit capability (Auch et al., 2022; Brown et al., 2022). However, spaceborne remote sensing data,  
40 especially for large-scale and coarse spatial resolution scenes, commonly suffer from the mixed pixel problem  
41 where the spatial unit of the image (i.e., the pixel) may contain multiple land cover types on the ground. This  
42 makes the goal of conventional hard classification (i.e., one pixel one class) ill-defined, resulting in inaccurate  
43 boundaries and loss of distinct land cover types in thematic maps produced by this approach (Atkinson, 2009).  
44 Soft classification methods (e.g., spectral unmixing) can represent the multiple classes within pixels as  
45 proportions (Shi and Wang, 2014; Pfoch et al., 2023). Specifically, in spectral unmixing, classes are  
46 represented by endmembers (pure spectral signatures of different land cover types), and each mixed pixel in the  
47 scene is decomposed into proportions of these endmembers (Keshava, 2003; Plaza et al., 2011). However, the  
48 spatial position of each class *within* each pixel remains unknown in the coarse proportions, and it can be  
49 challenging to present such information in a single thematic map when the number of classes is large (Wang et

50 al., 2014b). Subpixel mapping (SPM), also termed super-resolution mapping, is an effective solution to this  
51 issue. SPM can reveal the nature of class mixing (Fisher, 1997), encompassing both the land cover composition  
52 and the spatial arrangement of the classes within the mixed pixels.

53 Generally, the SPM approach divides pixels into smaller units (i.e.,  $s \times s$  subpixels,  $s$  is the zoom factor) and  
54 assigns class labels to these units such as to map land cover at the finer spatial resolution. Due to the existence  
55 of multiple solutions to the spatial distribution within mixed pixels, SPM is inherently an ill-posed problem. To  
56 tackle this inverse problem, SPM relies on two core pillars: spatial prior and data fidelity. In essence, the spatial  
57 prior term specifies the rules for allocating land cover classes at the desired fine spatial resolution, thereby,  
58 reducing the space of possible solutions directly. Existing SPM methods focus predominantly on investigating  
59 various spatial prior terms, mainly through two streams. The first, spatial dependence or attraction, assumes  
60 that similar land cover classes tend to be located closer together. Conventional methods in this stream include  
61 the pixel swapping algorithm (PSA) (Atkinson, 2005), Hopfield neural network (HNN) (Tatem et al., 2002),  
62 Markov random field (MRF) (Kasetkasem et al., 2005) and radial basis function (RBF) (Wang et al., 2014a).  
63 The second stream aims to regularize the ill-posed problem by extending the spatial prior term through adding  
64 guidance on spatial details, involving panchromatic images (Nguyen et al., 2011), digital elevation models  
65 (Ling et al., 2008), seed labeled points (Chen et al., 2023), Google Earth images (He et al., 2022), temporally  
66 adjacent fine land cover maps (Li et al., 2021; Wang et al., 2022; Zhang et al., 2022), and coarse-to-fine image  
67 patches (Shang et al., 2020; Zhang et al., 2023). This type of spatial prior is effective and appealing when  
68 accessible. However, acquisition of the ancillary data is often laborious, and uncertainties may arise, such as  
69 registration error, scale difference and land cover changes over time.

70 The second pillar of SPM, the data fidelity term, is conventionally constructed through coarse proportion  
71 constraints, a universal strategy adopted by most SPM methods. Specifically, the underlying principle is that  
72 the number of subpixels for each land cover class within the coarse pixels should conform to predefined  
73 proportions. This coarse proportion information is generally extracted by applying spectral unmixing to the  
74 original coarse spatial resolution multi-spectral images, implying that spectral unmixing serves as a

75 pre-processing step for SPM. However, as a widely acknowledged open issue, spectral unmixing-predicted  
76 proportions, for input to SPM, are not error-free (Dong et al., 2022). For example, the PSA and RBF methods,  
77 which adhere strictly to the coarse proportions, generate noise-like erroneously labeled subpixels when errors  
78 exist in the proportions. To handle this situation, certain SPM approaches adopt a more lenient interpretation of  
79 the coarse proportions constraint to obtain a more smoothed result. For example, MRF imports a spectral  
80 constraint term to balance data fidelity between the real spectral images and the proportion constraints.  
81 Additionally, the HNN model employs soft values (ranging from 0 to 1) instead of hard labels (certain to be 0  
82 or 1) to represent class probabilities for each subpixel. These methods can partially mitigate minor noise-like  
83 erroneous subpixels in the SPM process. However, they fall short of dealing fully with proportion-dependent  
84 error in the SPM results. Moreover, the misclassified subpixels brought by errors in the coarse proportions  
85 have a negative effect on the spatial prior term of SPM.

86 To circumvent the reliance on spectral unmixing results, He et al. (2021) proposed an end-to-end  
87 deep-learning-based framework for SPM that omits the intermediate spectral unmixing step, with more  
88 attention on a learning sub-scale spatial pattern prior. However, the outcomes show that land cover categories  
89 may not be retrieved without the coarse proportion constraints. In contrast, methods with proportion constraints  
90 can recover all the land cover classes of interest, but may inherit any proportional errors in the final fine land  
91 cover maps. Hence, it is imperative to provide reliable class proportions for more accurate SPM results.

92 To mitigate errors in the coarse proportions, Yin et al. (2023) introduced a fraction (i.e., proportion) error  
93 eliminating convolutional neural network (CNN) model. Using training data obtained by adding simulated  
94 Gaussian-distributed errors to error-free proportions obtained through degrading the target, the network  
95 enables learning about the proportional errors. To reduce shadow effects, Hao et al. (2023) optimized the  
96 proportions by incorporating water, vegetation and shadow index features. Wang et al. (2020) addressed the  
97 effect of the point spread function through a Gaussian convolution kernel, obtaining enhanced coarse  
98 proportions as input for SPM. However, traditional pixel-level interpretation of spectral signatures faces  
99 challenges when dealing with complex land cover structures (Borsoi et al., 2021). This challenge is

100 exacerbated when there is significant spectral variability among land cover classes, originating from variation  
101 in material properties, environmental conditions, illumination angles and sensor characteristics (Wang et al.,  
102 2016; Wang et al., 2022). Hence, it becomes necessary to explore information not only on the spectrum of  
103 individual pixels, but also from the perspective of spatial contextual information.

104 In the hard classification domain, object-based image analysis can be effective for extracting spatial  
105 contextual information with reduced sensitivity to noise and variation (Hao et al., 2024), yet challenges persist  
106 in addressing the mixed pixel problem. Within the SPM domain, the literature on object-based SPM models is  
107 limited. For example, Ling et al. (2012) refined building mapping by extracting the main orientation of each  
108 building object as a spatial prior. Chen et al. (2017) shifted the conventional class allocation strategy from  
109 subpixel or class units to an object level for soft-then-hard SPM methods (Wang et al., 2014b). Nevertheless,  
110 object-scale information in these methods is employed for allocating subpixels with proportion constraints,  
111 retaining errors from spectral unmixing. Consequently, as a crucial pre-processing step of SPM, spectral  
112 unmixing necessitates object-oriented analysis to fully utilize neglected spatial contextual information within  
113 remote sensing images.

114 Early developments in spectral unmixing generally exploited spectral information alone. Given that remote  
115 sensing images contain both spatial and spectral information (Xu et al., 2022), incorporating spatial  
116 information into spectral unmixing has gained increasing attention in recent years (Shi and Wang, 2014; Hong  
117 et al., 2024). Existing methods for integrating spatial information into spectral unmixing focus primarily on  
118 two aspects. First, in the step of endmember selection, spatial information is used to find the purest or most  
119 representative endmembers (Plaza et al., 2002; Deng and Wu, 2013) or to share endmember combinations  
120 within spatially homogenous regions (Zare et al., 2013). Second, in the step of coarse proportion estimation,  
121 spatial information is considered by maximizing the spatial coherence among adjacent neighbors (Borsoi et al.,  
122 2020; Cao et al., 2022). Overall, the utilization of spatial information has shown great potential for enhancing  
123 spectral unmixing. However, these methods are fundamentally pixel-wise methods for unmixing the original  
124 images, meaning that object-scale information in the unmixing results is not fully leveraged. Furthermore,

125 before the implementation of SPM, supervised spectral unmixing is typically conducted to obtain the input  
126 coarse proportions, which requires selection of endmembers. Unsupervised SPM models, which are more  
127 convenient and user-friendly, are rarely considered in existing methods.

128 This paper introduces an unsupervised and automatic object-based SPM (UO-SPM) model to enhance SPM  
129 for both mixed and pure pixels concurrently. The object-based analysis is applied following an unsupervised  
130 soft classification process to group coarse proportions into objects. Recognizing that mixed pixels are often  
131 located at the intersection areas of different land cover classes (edges of objects) in real geographical scenes, a  
132 morphological operation is implemented to discriminate pure pixels within objects and mixed pixels at the  
133 edges of objects. Subsequently, pure pixels are less likely to be misidentified, and more accurate pure spectral  
134 signatures are more likely to be utilized for the secondary spectral unmixing of the remaining mixed pixels.  
135 Ultimately, the proposed UO-SPM model, with its comprehensive analysis of object-scale, pixel-scale and  
136 subpixel-scale information, can increase the accuracy of spectral unmixing and ultimately SPM without  
137 requiring additional human input. The main contributions are three-fold. First, an object-based strategy is  
138 proposed for SPM. The UO-SPM model effectively detects mixed pixels through object-based analysis,  
139 specifically focusing on the edges of objects. These detected mixed pixels are further enhanced through a  
140 supervised secondary spectral unmixing process. Second, the proposed UO-SPM is an entirely automatic  
141 unsupervised SPM model, taking coarse spectral images as input to generate fine spatial resolution land cover  
142 maps without manual input. The proposed model is adaptable to various SPM algorithms utilizing coarse  
143 proportions as part of the data fidelity term and is validated on diverse conventional algorithms, including PSA,  
144 RBF, HNN and MRF. Third, the characterization of spatial dependence in SPM is shifted from the pixel level  
145 to the object level. With UO-SPM, pure pixel information within objects is further utilized as prior information  
146 when allocating land cover classes within mixed pixels.

147 The remainder of this paper is structured as follows. Section 2 outlines the flowchart of UO-SPM, followed  
148 by a comprehensive description of each stage, encompassing unsupervised soft classification, object-based  
149 identification of mixed and pure pixels, and spectral unmixing and SPM for the remaining mixed pixels.

150 Section 3 demonstrates the effectiveness of UO-SPM based on experimental results on three multi-spectral  
 151 datasets. Section 4 discusses open issues related to UO-SPM and Section 5 concludes the paper.

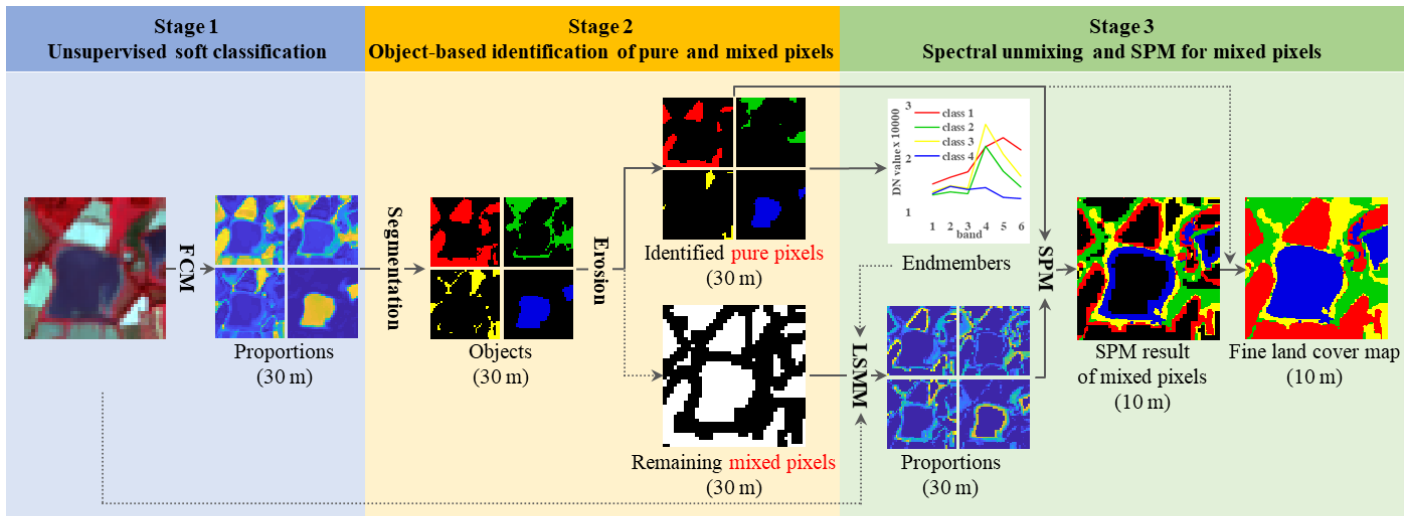
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## 154 2. Methods

155 The flowchart of the UO-SPM model is illustrated in Fig. 1 with three main stages. The detailed explanations  
 156 of each stage are provided below.

157



SPM: Subpixel mapping

FCM: Fuzzy C-Means algorithm (an unsupervised spectral unmixing method)

LSMM: Linear spectral mixture model (a supervised spectral unmixing method)

158

159 Fig. 1. Flowchart of the proposed unsupervised object-based subpixel mapping (UO-SPM).

160

### 161 2.1. Unsupervised soft classification

162 In the conventional SPM workflow, when dealing with a coarse spatial resolution multi-spectral image, the  
 163 initial step involves employing a spectral unmixing model to derive the coarse proportions. The LSMM,  
 164 chosen for its simplicity and physical interpretability, is applied widely as a pre-processing step in existing  
 165 SPM models (Olthof and Fraser, 2024). Then the coarse proportions are utilized directly in SPM, providing the  
 166 data coherence term. However, the spectral unmixing technique faces uncertainties in addressing the spectral

167 variation problem of land cover classes, irrespective of the chosen models, and errors inevitably impact the  
 168 SPM process negatively. In the proposed UO-SPM model, an unsupervised Fuzzy-C means (FCM) technique  
 169 is utilized to generate an initial soft classification result, forming the basis for subsequent object-based  
 170 analysis.

171 As shown in Fig. 1, the unsupervised FCM method is applied directly on the coarse spatial resolution  
 172 multi-spectral image. The FCM is essentially an unsupervised clustering algorithm with the objective of  
 173 minimizing the dissimilarity between data points (i.e., pixels) and cluster centers of land cover classes. Instead  
 174 of forcing to a specific cluster, FCM assigns membership degrees, which represent the probabilities of  
 175 belonging to each cluster. Given  $N$  pixels in the coarse spatial resolution multi-spectral image  $\mathbf{y}$ , the objective  
 176 function is defined as

$$\begin{aligned}
 177 \quad \min F &= \sum_{n=1}^N \sum_{k=1}^C (\mu_k(n))^m \|\mathbf{y}_n - \mathbf{v}_k\|^2 \\
 & \text{s.t. } \mu_k(n) \in [0,1], \sum_{k=1}^C \mu_k(n) = 1 \text{ and } \sum_{n=1}^N \mu_k(n) > 0
 \end{aligned} \tag{1}$$

178 in which  $C$  is the total number of clusters,  $m$  is a fuzziness index that determines the level of fuzziness,  $\mathbf{v}_k$  is  
 179 the center of cluster  $k$ , and  $\mu_k(n)$  is the membership degree of pixel  $n$  to cluster  $k$  with the constraints.

180 The fuzzy membership values generated by FCM exhibit correlation with the actual proportions of land  
 181 covers on the ground (Fisher and Pathirana, 1993). However, these values, while helpful in representing  
 182 individual pixels, often neglect the contextual information within objects. This oversight can result in large  
 183 errors in the spectral unmixing results. To address this limitation, a two-step object-oriented approach is  
 184 adopted. Initially, segmentation and erosion operations are applied to the fuzzy map predicted by FCM,  
 185 enhancing the delineation of object boundaries (introduced in Section 2.2). Subsequently, the mixed pixels  
 186 within these objects, characterized with reduced errors, undergo supervised spectral unmixing for increased  
 187 accuracy (introduced in Section 2.3).

188



## 189 2.2. *Object-based identification of pure and mixed pixels*

### 190 2.2.1. *Segmentation*

191 Segmentation is not applied directly to the original multi-spectral images, but rather to the FCM results for  
192 two primary reasons. First, FCM offers a representation of the uncertainty in the data, making it valuable for  
193 addressing regions with overlapping diverse land cover classes. Second, over- and under-segmentation can  
194 occur easily when applied to the original data, while FCM provides greater flexibility in handling clusters of  
195 various shapes. In this paper, the Otsu algorithm (Otsu, 1979) is employed to find the optimal threshold  
196 automatically for segmenting the coarse proportions into background and foreground objects for each land  
197 cover class. The Otsu algorithm operates on histogram-based principles with the goal of maximizing inter-class  
198 variance between two classes and minimizing the intra-class variance simultaneously. This aligns with the  
199 concept of coarse proportions with errors for each land cover class. Given one cluster of the FCM result, the  
200 optimal threshold is found by testing intensity levels that can maximize the inter-class variance.

### 202 2.2.2. *Pixel identification by morphological erosion*

203 Mixed pixels are generally located at the intersection of different land cover types, that is, the edge pixels of  
204 objects. Moreover, the Otsu algorithm may face challenges when the proportion of a certain class is small or  
205 when the background is complex (e.g. simultaneous presence of forest and grass classes). Therefore,  
206 morphological erosion is applied consecutively to exclude pixels located at the edge of objects, which are more  
207 likely to be mixed pixels. This approach effectively addresses the intra-spectral variability problem by  
208 identifying inner pixels of objects (more likely to be pure pixels) through the segmentation of the FCM results  
209 into objects, for each land cover class in the FCM results. Overall, this segmentation-then-erosion step is the  
210 key to coping with the problem of complex land cover structures with evitable spectral variation by fully  
211 utilizing the latent contextual object-based information in the coarse proportions.

### 2.3. Spectral unmixing and SPM for mixed pixels

#### 2.3.1. Spectral unmixing for remaining mixed pixels

The LSMM method is utilized, but plays distinct roles compared to FCM in the UO-SPM framework. Specifically, the FCM method serves as the foundation of the subsequent segmentation and erosion steps, while the purpose of utilizing LSMM is to further increase the unmixing accuracy of the identified remaining mixed pixels. In LSMM, the spectral response of a mixed pixel is viewed as a linear weighted sum of its component land cover spectra in that pixel, expressed by

$$\mathbf{y}_n = \sum_{k=1}^C \mathbf{E}_k f_k + \mathbf{e} \quad (2)$$

$$s.t. f_k \geq 0 \quad (k = 1, \dots, C) \text{ and } \sum_{k=1}^C f_k = 1$$

in which  $\mathbf{y}_n$  is the vector for spectral responses in  $B$  wavebands of a pixel  $n$ ,  $f_k$  is the proportional coverage of class  $k$  in the observed pixel and  $\mathbf{e}$  is a residual error term. The columns of  $\mathbf{E}_k$  represent pure spectra of the  $k$  land cover class in the absence of noise, commonly derived from pre-defined pure pixels. Once  $\mathbf{E}$  is defined, the mixture model can estimate the class composition  $f_k$  of a pixel from its spectral response  $\mathbf{y}_n$  subject to the constraints.

The endmember matrix  $\mathbf{E}$  is commonly derived from manual selection of pure pixels. However, this approach is laborious, making it unsuitable for mapping diverse regions in real-world scenes. In the UO-SPM, the endmembers are approximated by calculating for the filtered inner pixels of objects (more likely to be pure pixels) in the segmentation-then-erosion process. That is,  $\mathbf{E}$  is acquired readily from the identified pure pixels for each land cover class. Additionally, the identified pure pixels belonging to different land cover classes inherently exhibit inter-class spectral variability. Therefore, the extraction of pure spectra is abundantly accessible and more comprehensive for diverse regions compared to labor-intensive manual selection.

#### 2.3.2. SPM for the remaining mixed pixels

235 In general, SPM models use the spatial attraction and data fidelity terms to predict the fine spatial resolution  
 236 land cover map  $\hat{\mathbf{X}}$ , which can be formulated as

$$237 \quad \hat{\mathbf{X}} = \arg \max(A(\mathbf{X})) + \arg \min(D(\mathbf{X}, \mathbf{Y}, \mathbf{H})) \quad (3)$$

238 where  $\mathbf{Y} = [y_1^1, y_2^1 \dots y_N^1, y_1^2, y_2^2 \dots y_N^2 \dots y_N^C]$  denotes the coarse spatial resolution coarse proportion image with  $N$   
 239 pixels for  $C$  land cover classes,  $\mathbf{X} = [x_1, x_2, \dots, x_{s \times N}]$  is the resultant fine land cover map,  $A(\mathbf{X})$  is the summary  
 240 of spatial attraction between each subpixel in  $\mathbf{X}$  and its spatial neighbors,  $\mathbf{H}$  represents the degradation process  
 241 between  $\mathbf{X}$  and  $\mathbf{Y}$ , and  $D(\mathbf{X}, \mathbf{Y}, \mathbf{H}) = \|\mathbf{Y} - \mathbf{H}\mathbf{X}\|_2^2$ , which represents the data coherence between the predicted  
 242 fine land cover map and the coarse proportion.

243 In the proposed UO-SPM model, benefitting from the object-based pixel identification step, the two terms  
 244 can be expressed based on the identified pure objects and the remaining mixed pixels as:

$$245 \quad \hat{\mathbf{X}} = A(\mathbf{X}_{object}) + D(\mathbf{X}_{object}) + \arg \max(A(\mathbf{X}_{pixel}) + A(\mathbf{X}_{pixel-to-object})) + \arg \min(D(\mathbf{X}_{pixel}, \mathbf{Y}, \mathbf{H})) \quad (4)$$

246 in which  $\mathbf{X}_{object}$  and  $\mathbf{X}_{pixel}$  represent the detected pure pixels in objects and the remaining mixed pixels,  
 247 respectively, while  $A(\bullet)$  and  $D(\bullet)$  are the spatial attraction term and data fidelity term, respectively. Ideally,  
 248 the spatial attraction term of pure pixels in objects  $A(\mathbf{X}_{object})$  is maximized, yielding a zero value for  $D(\mathbf{X}_{object})$   
 249 if the detection of mixed and pure pixels is correct. Through the object-based analysis, pure pixels inside  
 250 objects are included after the erosion step, and the remaining mixed pixels are further decomposed by  
 251 supervised spectral unmixing. Thereby, prediction for the remaining pixels can utilize the object-scale  
 252 information (i.e., the settled inner pure pixels of objects) as a spatial prior to reduce the uncertainties in SPM, as  
 253 represented by the spatial dependence term  $A(\mathbf{X}_{pixel-to-object})$  in Eq. (4).

254 The UO-SPM is proposed to reduce errors in spectral unmixing through unsupervised object-based analysis,  
 255 and ultimately increase the accuracy of SPM. Thus, UO-SPM is a universal model instead of a specific SPM  
 256 algorithm. After detecting pure pixels and unmixing mixed pixels using the UO-based strategy, the final SPM

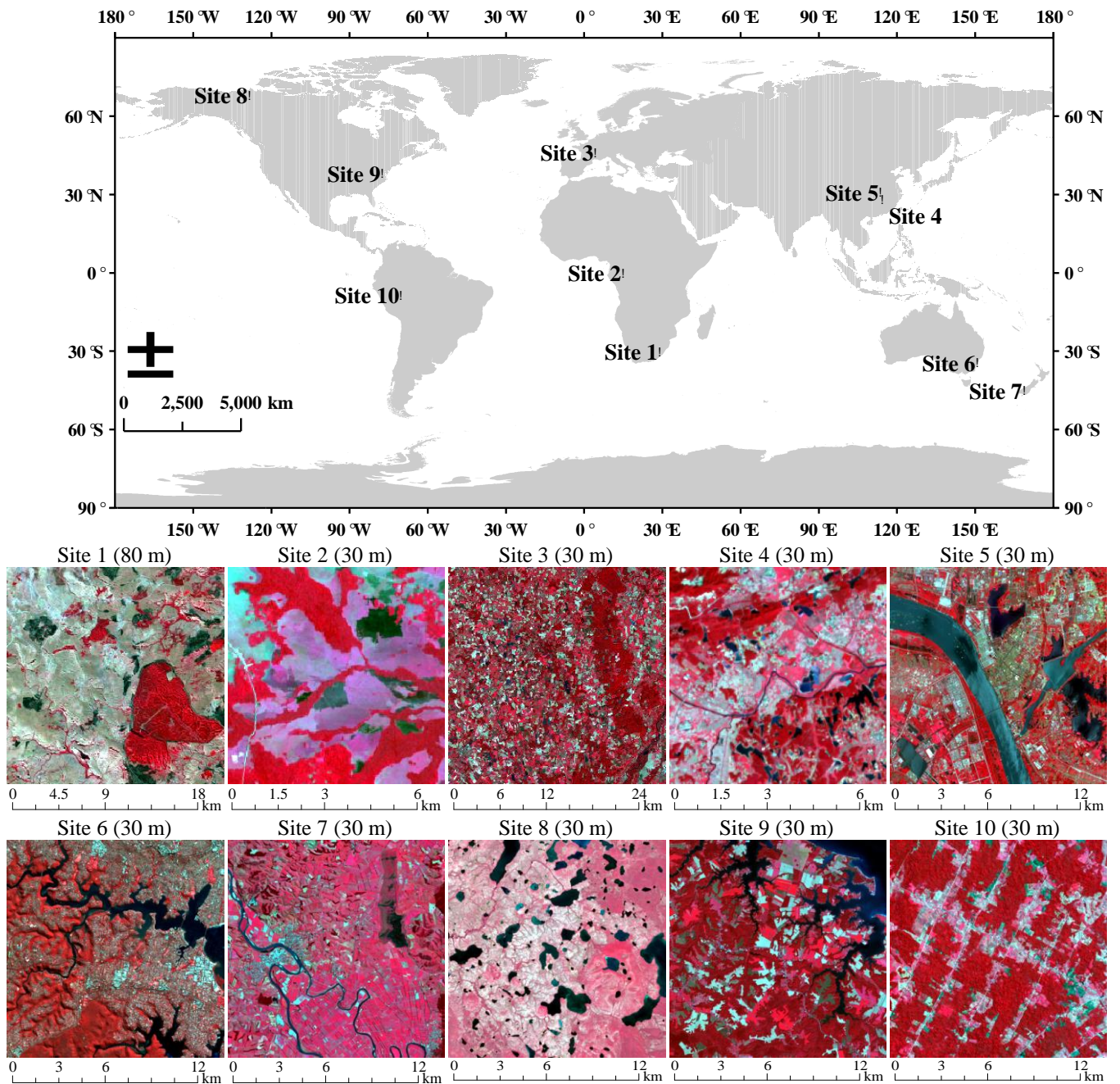
257 of the remaining mixed pixels can be conducted by any existing SPM methods that use spectral unmixing as a  
258 pre-processing step.

### 260 **3. Experiments**

#### 261 *3.1. Study area and datasets*

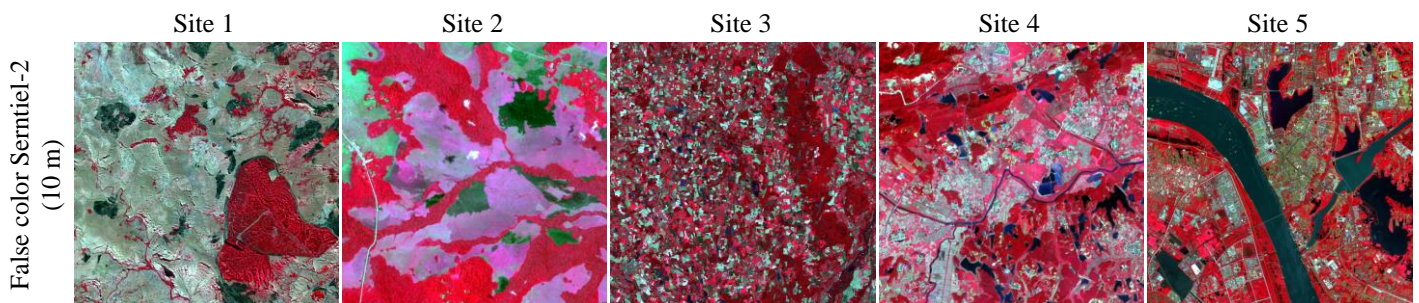
262 To evaluate the effectiveness of the proposed UO-SPM approach, experiments were conducted on 10 study  
263 sites (Fig. 2 and Table 1). The locations of these sites on the world map and their corresponding input coarse  
264 images are shown in Fig. 2. For Site 1, the 80 m coarse multi-spectral image used as input for SPM was derived  
265 by degrading a 10 m reference Sentinel-2 multi-spectral image acquired on July 3, 2019 with a scale factor of  
266 eight. For Sites 2-10, the 30 m multi-spectral Landsat images used as inputs for SPM were acquired from the  
267 United States Geological Survey (USGS) (<https://earthexplorer.usgs.gov/>). The center coordinates, acquisition  
268 dates, sizes of the input coarse images (i.e., 30 m Landsat) and 10 m Sentinel-2 reference images are listed in  
269 Table 1. For quantitative evaluation, the fine spatial resolution land cover maps (Lines 2 and 4 of Fig. 3) for the  
270 study areas were obtained using a support vector machine (SVM) applied to the temporally closest 10 m  
271 multi-spectral Sentinel-2 images (Lines 1 and 3 of Fig. 3) acquired from the Copernicus European Space  
272 Agency hub (<https://dataspace.copernicus.eu/>). The zoom factor of SPM was eight for Site 1 and three for Sites  
273 2-10.

274



275 Fig. 2. The locations of the 10 study sites on the world map and their corresponding input coarse spatial resolution images. The false  
 276 color coarse images are composed using Near-Infrared (NIR), Red and Green bands as RGB.

277



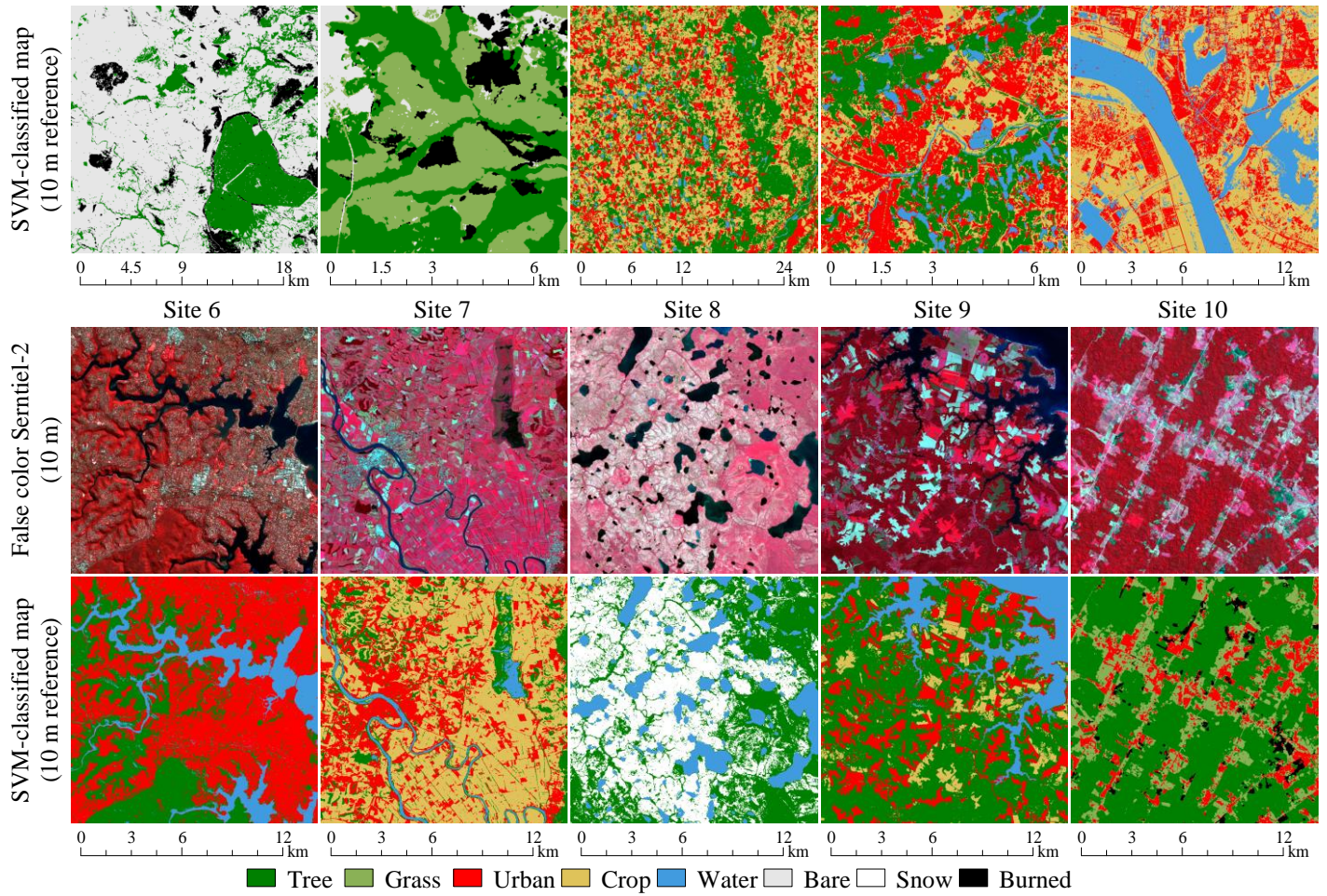


Fig. 3. The 10 m false-color Sentinel-2 images and the corresponding land cover maps derived with a support vector machine (SVM) used for accuracy assessment.

Table 1 Detailed information of the 10 study sites

Site	Center coordinates		Source of input coarse multi-spectral images	Acquisition date of Coarse images (Month/Day/Year)	Size of coarse images	Acquisition date of Sentinel-2 images (Month/Day/Year)	Size of fine reference land cover maps	Zoom factor of SPM
1	30°17' S	29°50' E	Degraded Sentinel-2	07/03/2019	225×225	07/03/2019	1800×1800	8
2	0°17' S	15°46' E	Landsat 8	09/07/2022	200×200	09/07/2022	600×600	3
3	46°03' N	5°10' E	Landsat 9	10/06/2023	800×800	10/06/2023	2400×2400	3
4	28°08' N	115°16' E	Landsat 9	10/16/2023	200×200	10/16/2023	600×600	3
5	30°28' N	114°33' W	Landsat 8	06/08/2023	400×400	06/09/2023	1200×1200	3
6	34°01' S	151°4' E	Landsat 8	07/12/2023	400×400	07/13/2023	1200×1200	3
7	45°14' S	169°45' E	Landsat 9	01/07/2023	400×400	01/08/2023	1200×1200	3
8	67°58' N	127°28' W	Landsat 9	06/25/2023	400×400	06/25/2023	1200×1200	3
9	37°58' N	76°31' W	Landsat 9	10/02/2023	400×400	10/02/2023	1200×1200	3
10	8°48' S	69°22' W	Landsat 8	08/26/2023	400×400	08/27/2023	1200×1200	3

### 3.2. Benchmark methods and evaluation indices

As previously mentioned, the UO-SPM model can be integrated with any SPM method that uses spectral unmixing as a pre-processing step. The UO-SPM model addresses errors in spectral unmixing through unsupervised object-based analysis. To validate the benefits of the unsupervised object-based (UO) analysis, we examined the performance of UO-SPM using four conventional SPM algorithms, including HNN, MRF, PSA and RBF. These methods exhibit distinct characteristics in terms of spatial and data fidelity terms. At the object-scale, subpixels within the inner part of objects (i.e., identified pure pixels) are assigned to their corresponding class across all SPM methods. Regarding the pixel-scale information (i.e., coarse proportions of the remaining mixed pixels), the HNN and MRF methods do not adhere strictly to the coarse proportions, while PSA and RBF comply strictly with the coarse proportions. Moreover, the object scale information (i.e., subpixels that are assigned to one class already) aids in predicting the remaining subpixels through the spatial attraction term. This term is defined between subpixels and subpixels for methods including MRF, HNN and PSA, while for RBF it operates between subpixels and pixels. More details can be found for PSA in Atkinson (2005), HNN in Nguyen et al. (2006), MRF in Tolpekin and Hamm (2008) and RBF in Wang et al. (2014a). Moreover, the morphological filtering and fraction refilling (MFFR) algorithm (Ling et al., 2014) was used as a benchmark, involving interpolation, morphological operations (e.g., erosion or opening) and final optimization of the SPM result.

For comparison, the original unsupervised FCM and supervised LSMM were also implemented for the four SPM algorithms. In summary, 16 methods were examined, namely, UO-HNN, UO-MRF, UO-PSA, UO-RBF, FCM-HNN, FCM-MRF, FCM-PSA, FCM-RBF, FCM-MFFR-erode, FCM-MFFR-open, LSMM-HNN, LSMM-MRF, LSMM-PSA, LSMM-RBF, FCM-MFFR-erode and LSMM-MFFR-open. Note that the MFFR method is a type of object-based method. Therefore, it was not integrated into the UO-based model and compared with the UO-SPM methods directly. During the experiments, the parameters for all methods were set empirically or based on suggestions from the existing literature. Specifically, the window size was set to  $3 \times 3$  subpixels for MRF and HNN,  $5 \times 5$  subpixels for PSA and MFFR, and  $3 \times 3$  pixels for RBF. The morphological

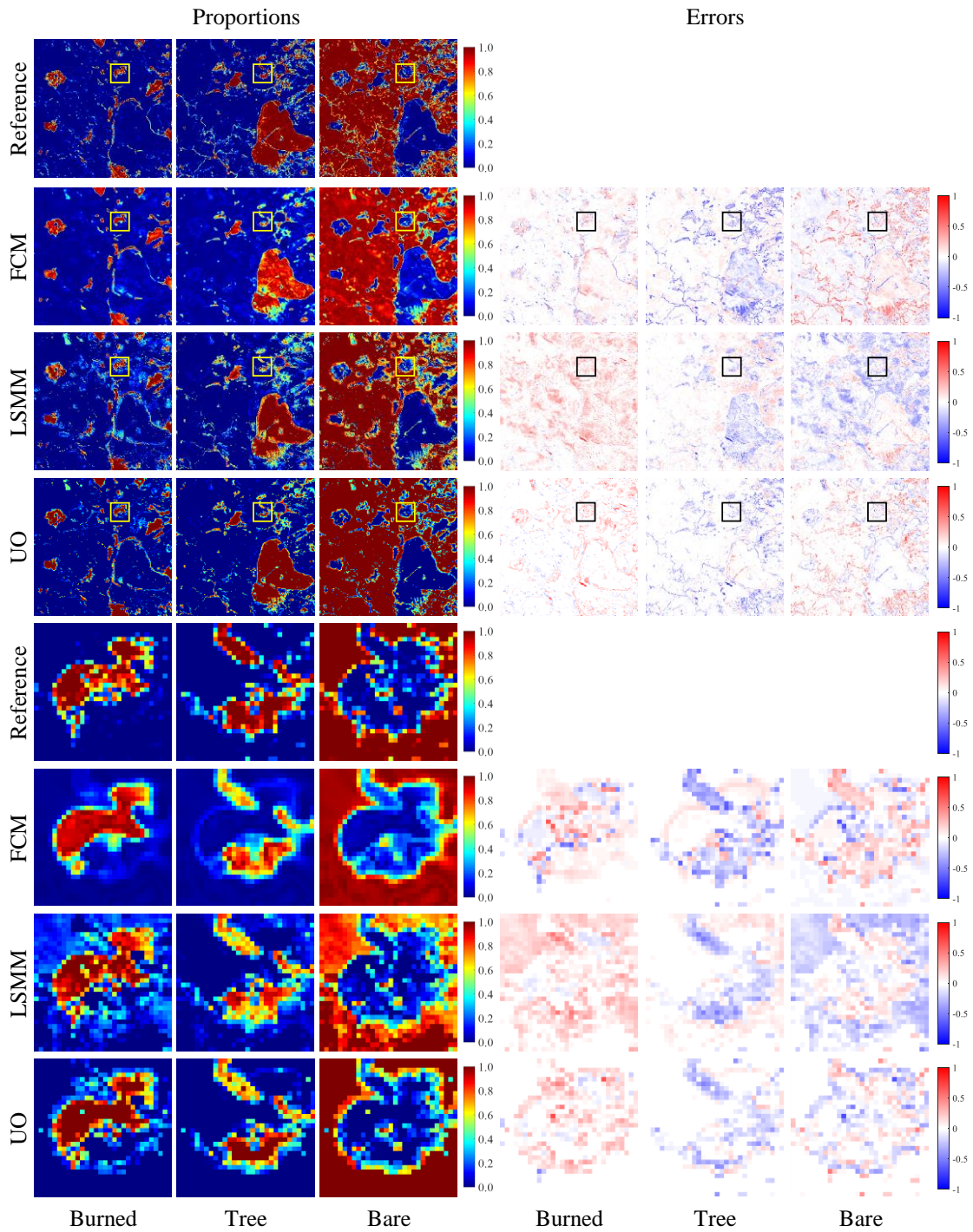
309 structure size was set to 3 for the UO-based methods (i.e., UO-HNN, UO-MRF, UO-PSA and UO-RBF) and  
310 the MFFR-based methods (i.e., FCM-MFFR-erode, FCM-MFFR-open, LSMM-MFFR-erode and  
311 LSMM-MFFR-open).

### 313 *3.3. Spectral unmixing results*

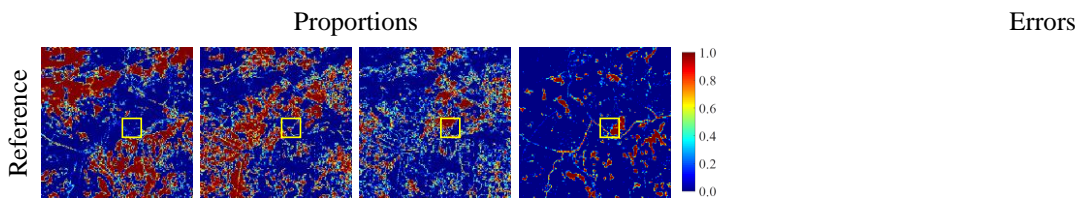
314 The proposed UO-SPM model addresses errors caused by the spectral unmixing process. Consequently, it is  
315 crucial to assess the coarse proportions with and without considering the object-based analysis. To this end, the  
316 UO-based spectral unmixing results were compared to those obtained using the FCM and LSMM methods.

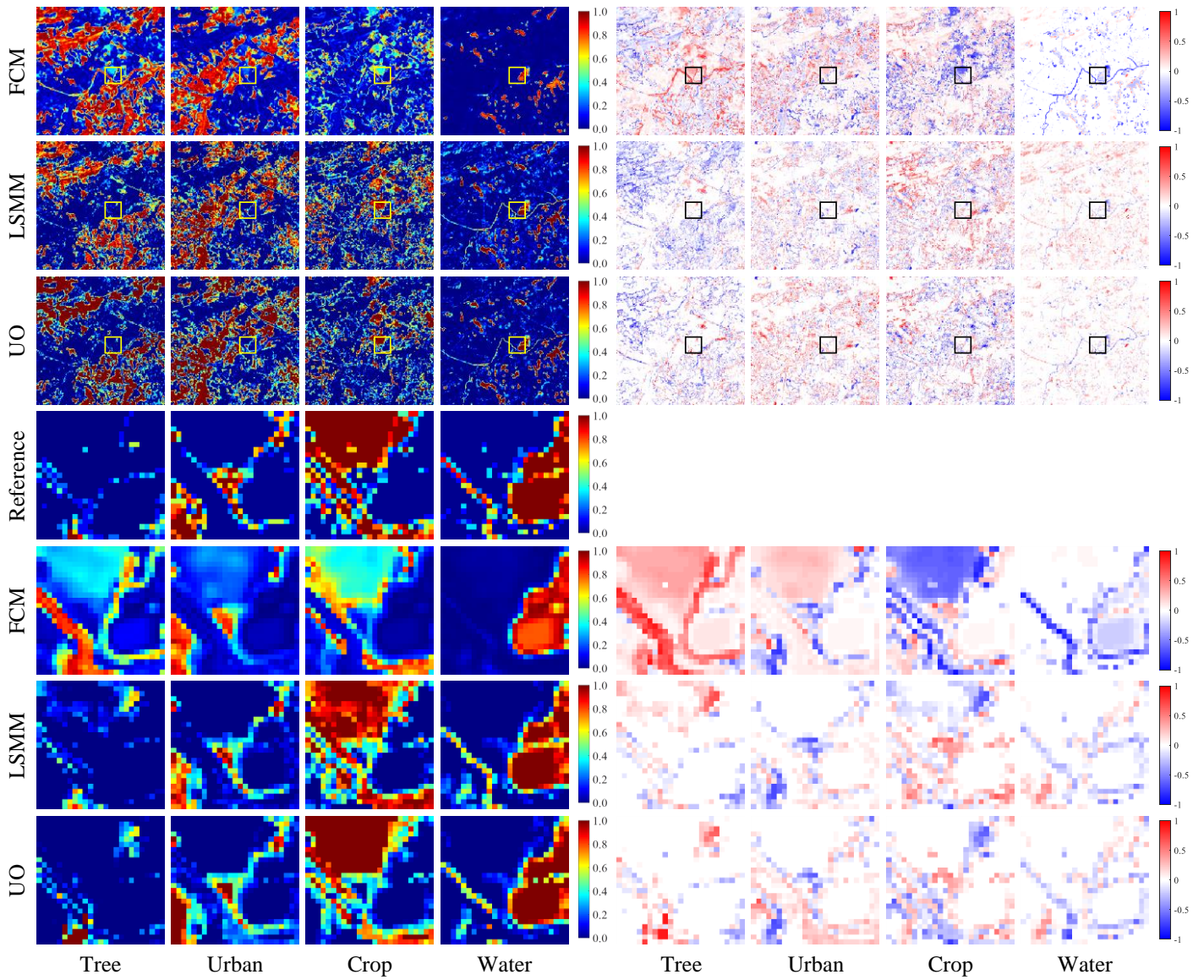
317 For visual comparison, the spectral unmixing results and error images for sites 1, 4 and 9, presented in Figs.  
318 4-6, respectively, reveal noteworthy distinctions among the three methods. The error images were generated by  
319 comparing the spectral unmixing results to the ideal proportions, with the latter derived by degrading the  
320 SVM-based fine spatial resolution land cover map with the corresponding zoom factor for each site. The  
321 second line in Figs. 4-6 depicts the results produced by the FCM-based spectral unmixing method. Clustering  
322 pixels with spectral similarity tends to generate ambiguous and over-smoothed proportion images at the  
323 boundaries of land cover classes. The third line displays the results obtained through LSMM, revealing  
324 numerous noise pixels in the backgrounds of the land cover classes, misidentified as mixed pixels. In contrast,  
325 the UO-derived unmixing results, depicted in the fourth line, exhibit proportions that are closer to the ideal  
326 proportions, particularly for the inner regions of objects. The error images indicate that the FCM and LSMM  
327 results generally exhibit larger errors, with more pixels displaying both overestimated and underestimated  
328 proportion errors. The error images in Figs. 4-6 reveal a larger number of error pixels with deeper colors in the  
329 FCM and LSMM results compared to those of the UO results. In summary, visual comparison between the  
330 coarse proportions and error images emphasizes that the proportion error is the smallest for the object-based  
331 analysis in the UO-SPM framework, outperforming the other two spectral unmixing methods.



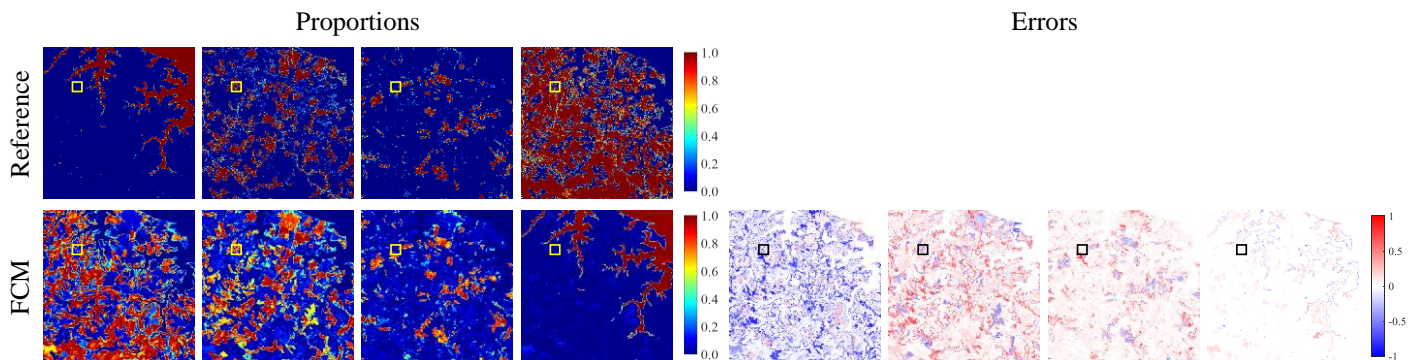


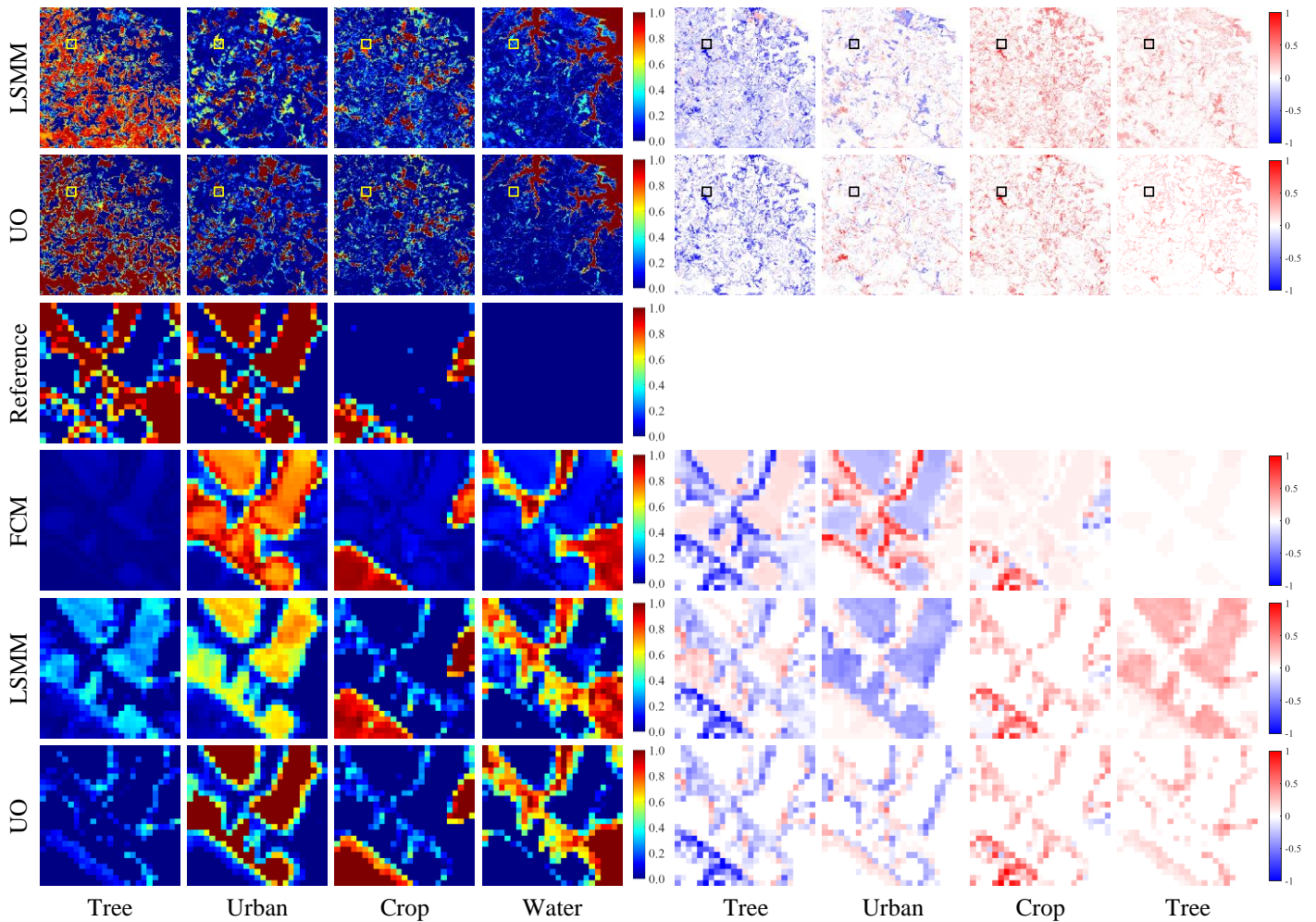
334 Fig. 4. Spectral unmixing results, corresponding proportion error maps (compared to the ideal coarse proportions derived by  
 335 degrading the reference land cover map with a zoom factor of three) and zoom-in scenes for site 1 (with a zoomed subarea in the last  
 336 four lines).





337 Fig. 5. Spectral unmixing results, corresponding proportion error maps (compared to the ideal coarse proportions derived by  
 338 degrading the reference land cover map with a zoom factor of three) and zoom-in scenes for Site 4 (with a zoomed subarea in the last  
 339 four lines).  
 340





341 Fig. 6. Spectral unmixing results, corresponding proportion error maps (compared to the ideal coarse proportions derived by  
 342 degrading the reference land cover map with a zoom factor of three) and zoom-in scenes for Site 9 (with a zoomed subarea in the last  
 343 four lines).  
 344

345 Quantitative evaluation of the spectral unmixing results for the 10 sites was conducted based on the  
 346 correlation coefficient ( $R$ ), root-mean-square-error (RMSE) and mean-absolute-error (MAE) between the  
 347 spectral unmixing results and the ideal coarse proportions (obtained by degrading the reference land cover map  
 348 with the zoom factor of each site). For clearer comparison, the differences in  $R$ , RMSE and MAE between the  
 349 spectral unmixing results of the UO and FCM (denoted as ‘UO than FCM’) and those of the UO and LSMM  
 350 (denoted as ‘UO than LSMM’) are listed in Table 2, as highlighted in bold.

351 In alignment with the visual evaluation presented in Figs. 4-6, the results for the LSMM surpass those of  
 352 FCM, with larger  $R$  and smaller RMSE and MAE values. This suggests that the resulting coarse proportions

generated by unsupervised FCM are less accurate than LSMM. Moreover, the UO method produces the most accurate coarse proportions across the 10 sites, as indicated by the largest  $R$ , and smallest RMSE and MAE values overall. More precisely, the  $R$  value of the UO method surpasses that of the FCM and LSMM results by an average of 3.65% and 1.10%, respectively. The MAE and RMSE values of UO are decreased by an average of 15.22% (an absolute decrease of 0.0302) and 37.33% (an absolute decrease of 0.0453), respectively, compared to those of the FCM method. Compared to the LSMM method, the MAE and RMSE values of the UO method are decreased by an average of 5.65% (an absolute decrease of 0.0101) and 24.74% (an absolute decrease of 0.0250), respectively.

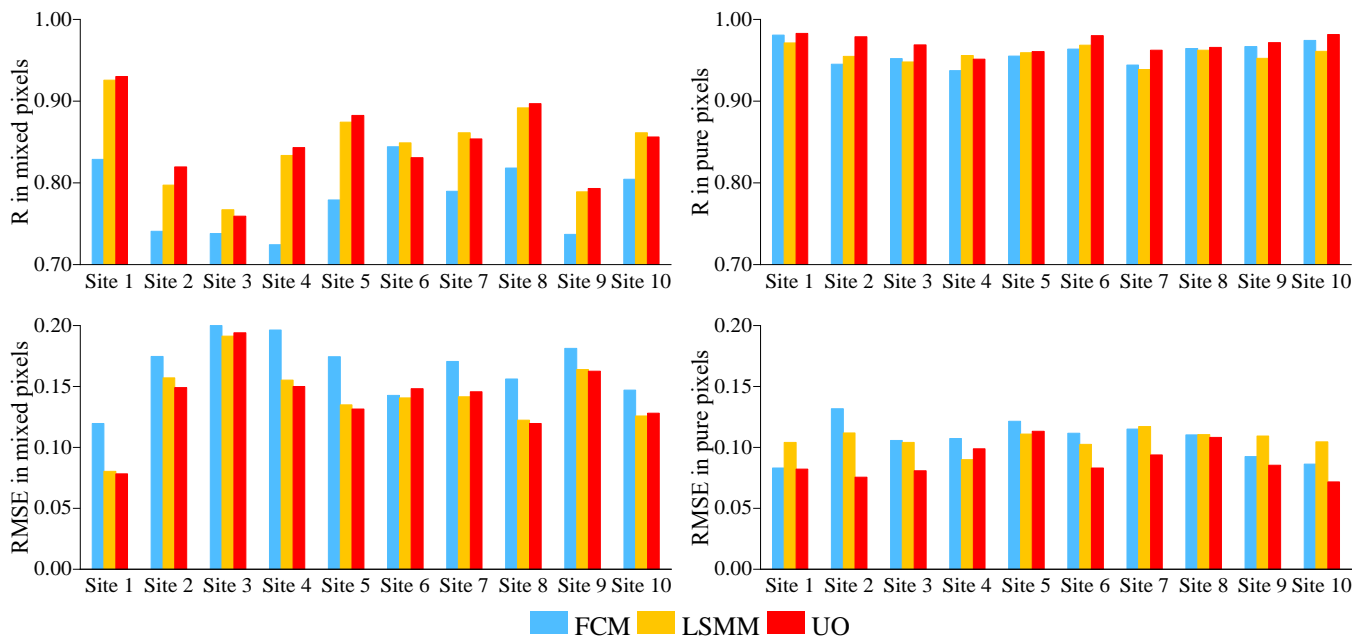
Table 2 Accuracy assessment of spectral unmixing results for the 10 sites based on correlation coefficient ( $R$ ), root-mean-square-error (RMSE) and mean-absolute-error (MAE) compared to ideal coarse proportions

Index	Method	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 8	Site 9	Site 10
$R$	FCM	0.9416	0.8605	0.8266	0.8030	0.8656	0.9092	0.8595	0.8982	0.8665	0.9112
	LSMM	0.9551	0.8875	0.8398	0.8778	0.9111	0.9162	0.8895	0.9255	0.8760	0.9191
	UO	0.9663	0.9161	0.8518	0.8807	0.9127	0.9206	0.9012	0.9297	0.8936	0.9344
	<b>UO than FCM</b>	<b>0.0247</b>	<b>0.0556</b>	<b>0.0252</b>	<b>0.0777</b>	<b>0.0471</b>	<b>0.0114</b>	<b>0.0417</b>	<b>0.0315</b>	<b>0.0271</b>	<b>0.0232</b>
	<b>UO than LSMM</b>	<b>0.0112</b>	<b>0.0286</b>	<b>0.0120</b>	<b>0.0029</b>	<b>0.0016</b>	<b>0.0044</b>	<b>0.0117</b>	<b>0.0042</b>	<b>0.0176</b>	<b>0.0153</b>
RMSE	FCM	0.1456	0.2187	0.2272	0.2238	0.2126	0.1813	0.2056	0.1912	0.2035	0.1706
	LSMM	0.1315	0.1928	0.2177	0.1795	0.1747	0.1739	0.1838	0.1648	0.1970	0.1635
	UO	0.1135	0.1671	0.2102	0.1797	0.1736	0.1698	0.1732	0.1613	0.1835	0.1467
	<b>UO than FCM</b>	<b>-0.0321</b>	<b>-0.0516</b>	<b>-0.017</b>	<b>-0.0440</b>	<b>-0.039</b>	<b>-0.0115</b>	<b>-0.0324</b>	<b>-0.0299</b>	<b>-0.0200</b>	<b>-0.0239</b>
	<b>UO than LSMM</b>	<b>-0.0180</b>	<b>-0.0257</b>	<b>-0.0075</b>	<b>0.0002</b>	<b>-0.0011</b>	<b>-0.0041</b>	<b>-0.0106</b>	<b>-0.0035</b>	<b>-0.0135</b>	<b>-0.0168</b>
MAE	FCM	0.0828	0.1423	0.1465	0.1388	0.147	0.1146	0.1264	0.1147	0.1105	0.0898
	LSMM	0.0801	0.1045	0.1300	0.1011	0.1062	0.1017	0.1033	0.0895	0.1085	0.0854
	UO	0.0483	0.0652	0.1051	0.0920	0.0865	0.0794	0.0785	0.0696	0.0798	0.0560
	<b>UO than FCM</b>	<b>-0.0345</b>	<b>-0.0771</b>	<b>-0.0414</b>	<b>-0.0468</b>	<b>-0.0605</b>	<b>-0.0352</b>	<b>-0.0479</b>	<b>-0.0451</b>	<b>-0.0307</b>	<b>-0.0338</b>
	<b>UO than LSMM</b>	<b>-0.0318</b>	<b>-0.0393</b>	<b>-0.0249</b>	<b>-0.0091</b>	<b>-0.0197</b>	<b>-0.0223</b>	<b>-0.0248</b>	<b>-0.0199</b>	<b>-0.0287</b>	<b>-0.0294</b>

Since the aim of the UO strategy is to reduce spectral unmixing errors by identifying mixed and pure pixels, the mixed and pure pixels are assessed separately. Fig. 7 illustrates these assessments on the 10 sites based on the  $R$  and RMSE between the coarse proportions and ideal proportions. As shown in Fig. 7, the UO strategy generally produces the largest  $R$  and the smallest RMSE among the three methods for both the mixed and pure pixels. Further, UO is more advantageous for pure pixels, producing a larger  $R$  and smaller RMSE compared to

370 those in mixed pixels. Specifically, compared to LSMM, the  $R$  value is increased by an average of 0.14% and  
 371 the RMSE value is decreased by an average of 0.52% in mixed pixels across the 10 sites. For pure pixels, the  $R$   
 372 value is increased by an average of 1.32% and the RMSE value is decreased by an average of 15.79% across  
 373 the 10 sites. This suggests that the segmentation step can effectively reduce the likelihood for pure pixels to be  
 374 misidentified as mixed pixels.

375



376

377 Fig. 7. Correlation coefficient ( $R$ ) and root-mean-square-error (RMSE) of coarse proportions in mixed and pure pixels compared to  
 378 the corresponding ideal coarse proportions for the 10 study sites.

379

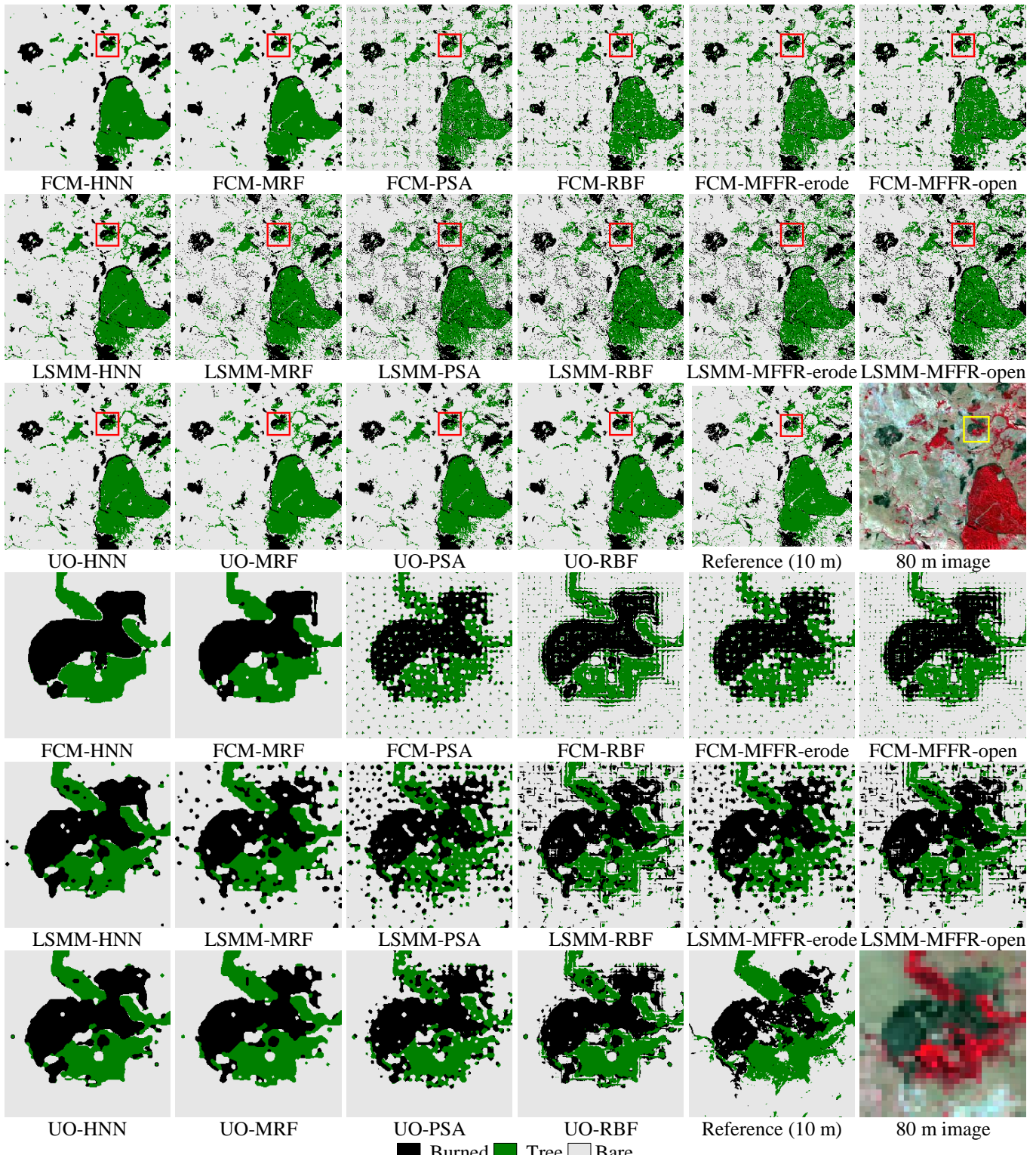
### 380 3.4. SPM results

381 As a general model, UO-SPM was evaluated in four forms, that is by combining with four SPM methods,  
 382 namely UO-HNN, UO-MRF, UO-PSA and UO-RBF. Simultaneously, six standard SPM methods (HNN,  
 383 MRF, PSA, RBF, MFFR-open and MFFR-erode) were applied to two types of coarse proportions obtained by  
 384 the FCM and LSMM method to provide 12 benchmarks for the UO-SPM results. Figs. 8-10 display the 16  
 385 SPM results, with a zoom factor of eight for site 1 and of three for sites 4 and 9. The zoomed coarse images for  
 386 the three sites are also depicted in Figs. 8-10.

387 Firstly, the results of the UO-based methods (i.e., UO-HNN, UO-MRF, UO-PSA and UO-RBF, see line 4 of  
388 Figs. 8-10) that consider proportions based on object-based analysis, exhibit a significantly closer alignment  
389 with the reference images compared to those of the FCM- and LSMM-based methods (i.e., methods prefixed  
390 with FCM and LSMM, see lines 2-3 of Figs. 8-10). Specifically, the UO-based methods demonstrate  
391 remarkable improvements in restoring large-sized objects with more continuous boundaries, and exhibit fewer  
392 speckle artifacts for all datasets, as seen in the zoomed images of Figs. 8-10. Additionally, the LSMM-based  
393 methods can generate more details of small objects than the FCM-based methods, but at the cost of producing  
394 scattered noise. Overall, the proposed UO-SPM framework is effective for the various SPM methods,  
395 outperforming the original SPM methods that use FCM- and LSMM-derived proportions.

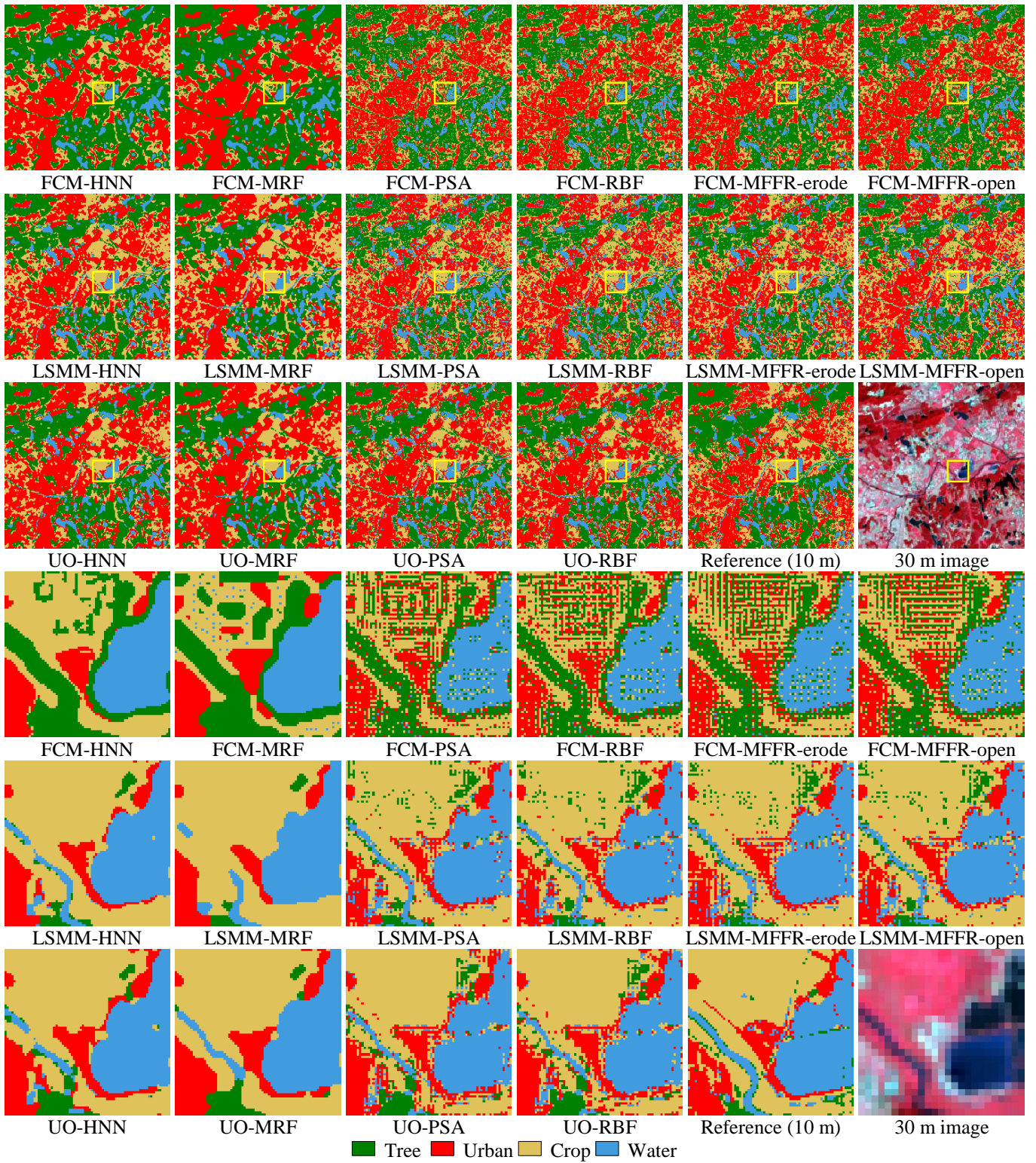
396 Secondly, with the same spectral unmixing methods, the HNN- and MRF-based methods present smoother  
397 and visually more appealing results than those of the PSA-, RBF- and MFFR-based methods, while the PSA-,  
398 RBF- and MFFR-based methods tend to produce speckle-like artifacts, especially at the boundaries of objects.  
399 This because the MRF and HNN can eliminate small amounts of noise through the spatial smoothing term  
400 without perfectly conforming to the coarse proportions. It is noteworthy that, through object-based analysis,  
401 the UO-PSA and UO-RBF methods also mitigate errors obviously in the inner parts of objects compared to the  
402 results of LSMM-PSA and LSMM-RBF. Moreover, although morphological operations were considered in the  
403 MFFR method, the refilling process of MFFR still complies to the coarse proportions. Overall, as errors in  
404 spectral unmixing are inevitable in real applications, the UO-MRF and UO-HNN would be more suitable for  
405 land cover mapping among the 16 SPM methods in practice.

406 In conclusion, all of the UO-SPM-based methods reconstruct more accurate results than the FCM- and  
407 LSMM-based versions for both large-sized and small-sized land cover classes. Furthermore, the comparison  
408 between different SPM methods reveals that the SPM methods strictly satisfying the coarse proportion  
409 constraints (i.e., PSA and RBF) can be notably enhanced within the UO-SPM framework. Meanwhile, the  
410 UO-MRF and UO-HNN produce visually more accurate predictions than PSA, RBF and MFFR-based  
411 methods.



412  
413  
414

Fig. 8. SPM results for Site 1 (with a zoomed subarea in the last three lines).

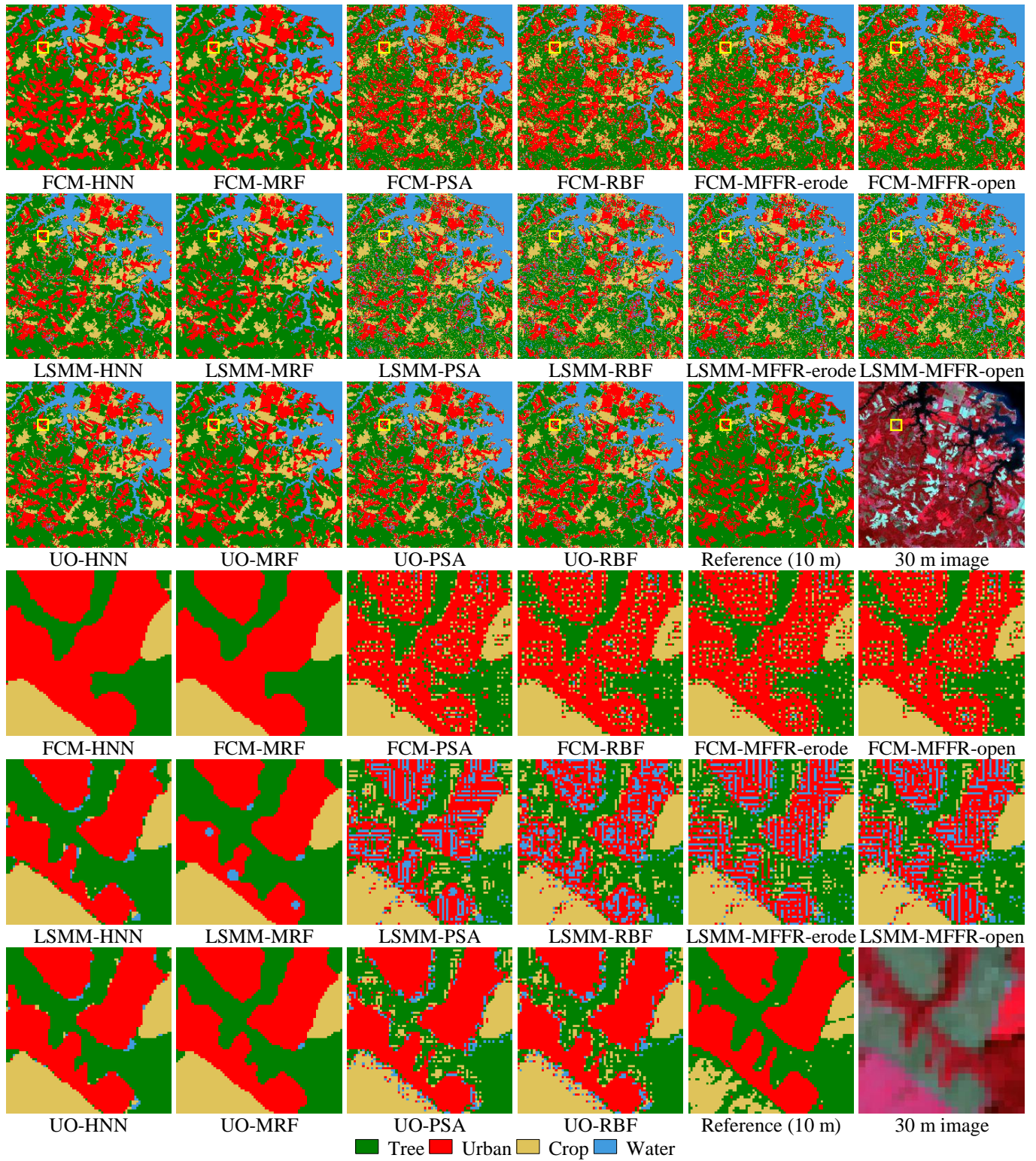


415

416 Fig. 9. SPM results for Site 4 (with a zoomed subarea in the last three lines).

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418

419 Fig. 10. SPM results for Site 9 (with a zoomed subarea in the last three lines).

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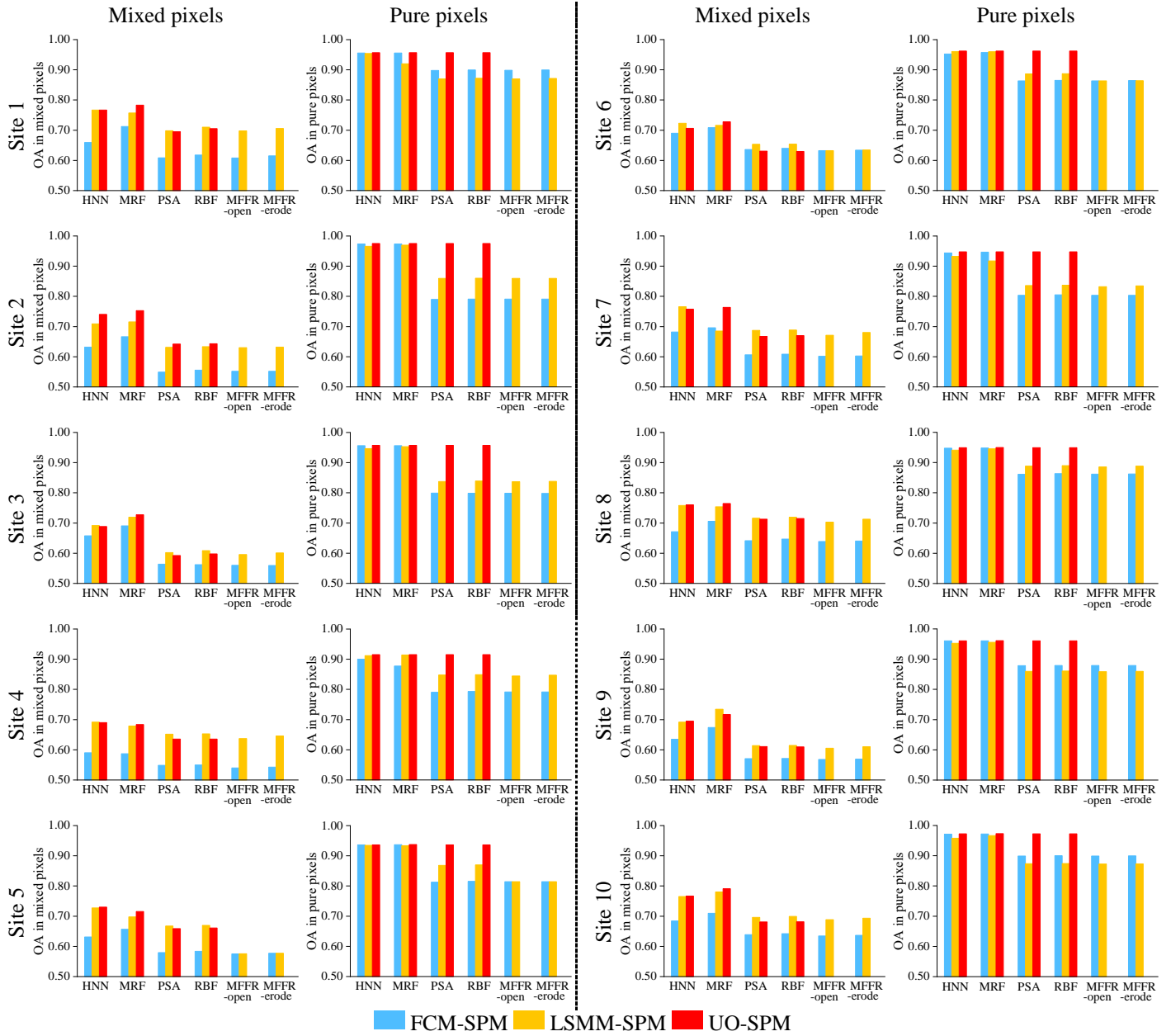
Table 3 Overall accuracy (OA) of SPM results for the 10 sites

	Methods	HNN	MRF	PSA	RBF	MFFR-erode	MFFR-open
Site 1	FCM-SPM	0.8949	0.9058	0.8385	0.8414	0.8387	0.8408
	LSMM-SPM	0.9154	0.8864	0.8344	0.8387	0.8344	0.8375
	UO-SPM	0.9176	<b>0.9211</b>	0.9028	0.9050		
Site 2	FCM-SPM	0.8545	0.8665	0.7061	0.7092	0.7079	0.7077
	LSMM-SPM	0.8766	0.8814	0.7801	0.7811	0.7796	0.7805
	UO-SPM	0.8933	<b>0.8977</b>	0.8590	0.8593		
Site 3	FCM-SPM	0.8020	0.8189	0.6775	0.6765	0.6752	0.6748
	LSMM-SPM	0.8148	0.8321	0.7158	0.7199	0.7122	0.7155
	UO-SPM	0.8183	<b>0.8385</b>	0.7686	0.7714		
Site 4	FCM-SPM	0.7354	0.7230	0.6620	0.6637	0.6578	0.6592
	LSMM-SPM	0.7950	0.7889	0.7436	0.7448	0.7343	0.7401
	UO-SPM	<b>0.7954</b>	0.7920	0.7664	0.7665		
Site 5	FCM-SPM	0.8239	0.8334	0.7266	0.7302	0.7260	0.7270
	LSMM-SPM	0.8582	0.8465	0.7943	0.7959	0.7262	0.7269
	UO-SPM	<b>0.8603</b>	0.8554	0.8341	0.8348		
Site 6	FCM-SPM	0.8672	0.8763	0.7895	0.7919	0.7885	0.7896
	LSMM-SPM	0.8834	0.8809	0.8108	0.8113	0.7885	0.7896
	UO-SPM	0.8790	<b>0.8861</b>	0.8544	0.8542		
Site 7	FCM-SPM	0.8261	0.8338	0.7147	0.7168	0.7126	0.7133
	LSMM-SPM	0.8575	0.8130	0.7690	0.7701	0.7598	0.7653
	UO-SPM	0.8621	<b>0.8649</b>	0.8216	0.8227		
Site 8	FCM-SPM	0.8584	0.8700	0.7903	0.7934	0.7898	0.7906
	LSMM-SPM	0.8820	0.8836	0.8326	0.8347	0.8267	0.8315
	UO-SPM	0.8882	<b>0.8902</b>	0.8729	0.8736		
Site 9	FCM-SPM	0.8336	0.8489	0.7585	0.7590	0.7577	0.7580
	LSMM-SPM	0.8507	0.8693	0.7639	0.7644	0.7597	0.7622
	UO-SPM	0.8571	<b>0.8657</b>	0.8241	0.8238		
Site 10	FCM-SPM	0.8766	0.8852	0.8131	0.8151	0.8118	0.8129
	LSMM-SPM	0.8944	0.9049	0.8149	0.8164	0.8117	0.8140
	UO-SPM	0.9047	<b>0.9129</b>	0.8764	0.8766		

424

425 Table 3 lists the overall accuracy (OA) of the SPM methods combined with the FCM, LSMM and  
426 UO-derived proportions, delineated line-by-line for the 10 sites. Across all experiments, the OA values of  
427 UO-SPM consistently surpass those of the FCM and LSMM-based methods. Specifically, the OAs of the  
428 UO-PSA and UO-RBF methods exceed those of the FCM-PSA and LSMM-RBF by an average of about 9%  
429 and surpass those of the LSMM-PSA and LSMM-RBF by an average of about 5% for the 10 sites. Although  
430 the enhancement is less pronounced for the HNN and MRF methods, there is still an increase in OA compared  
431 to the results of the FCM-based and LSMM-based methods. More precisely, the OA of the UO-MRF method  
432 exceeds those of FCM-MRF and LSMM-MRF by 2.63% and 1.38%, respectively. For HNN, the OA of  
433 UO-HNN is 3.03% and 0.48% larger than FCM-HNN and LSMM-HNN, respectively. Furthermore, the  
434 UO-MRF produces the largest OA among all methods, with an average of 87.25%. The MFFR-erode and

435 MFFR-open methods exhibit OAs similar to RBF and PSA. Overall, the UO-SPM model is demonstrated to be  
 436 effective for all four SPM methods, achieving larger OAs compared to the original methods with both the FCM  
 437 and LSMM-derived proportions.  
 438



439  
 440 Fig. 11. Classification accuracies (in terms of OA) for mixed pixels and pure pixels for the 10 sites.

441  
 442 As pure and mixed pixels are handled differently in the SPM process, the accuracies of the two types of  
 443 pixels are analyzed separately for the 10 sites, as shown in Fig. 11. Incorporation of the UO-SPM model results

444 in an observable increase in OA for both mixed and pure pixels. This increase is more apparent for mixed  
445 pixels in the case of UO-HNN and UO-MRF, while for UO-PSA and UO-RBF, the enhancement is more  
446 apparent for pure pixels than for mixed pixels. For example, compared to FCM-HNN, the accuracies of mixed  
447 pixels are increased by 10.72%, 10.85% and 3.11%, and those of pure pixels by 0.09%, 0.15% and 0.07% for  
448 sites 1-3, respectively. Moreover, the OAs for mixed pixels are generally smaller than for pure pixels,  
449 reflecting the difficulty, but also importance, of addressing the mixed pixel problem.

## 451 **4. Discussion**

### 452 *4.1. Consideration of unsupervised FCM*

453 Since the initial step of UO-SPM involves unsupervised FCM, the reliability of the FCM results warrants  
454 consideration. In the proposed UO-SPM model, initial FCM-derived coarse proportions are used to identify  
455 mixed and pure pixels through a segmentation-then-erosion step, followed by secondary LSMM-based  
456 unmixing of the remaining mixed pixels using endmembers extracted by averaging the spectral values of all  
457 filtered pure pixels (i.e., a global LSMM strategy that uses the same endmembers for all pixels). Thus, the  
458 initial FCM step might affect the identification of mixed and pure pixels and subsequently affect the accuracy  
459 of secondary spectral unmixing. To evaluate this, the spectral unmixing results of the original UO strategy  
460 were compared to two other versions, as listed in Table 4. Specifically, ‘FCM-global’ denotes the original UO  
461 strategy that conducts the segmentation-then-erosion step on the FCM-derived coarse proportions, followed by  
462 global LSMM for the remaining mixed pixels (i.e., the proposed scheme). ‘LSMM-global’ involves  
463 conducting the segmentation-then-erosion step on the LSMM-derived coarse proportions and then  
464 decomposing the identified mixed pixels using global LSMM. ‘FCM-local’ denotes conducting a  
465 segmentation-then-erosion step on the FCM results, followed by local LSMM that uses different endmembers  
466 for each pixel, which are extracted from its surrounding pure pixels.

Table 4 Comparison of three spectral unmixing strategies based on the  $R$ , RMSE and MAE between the results and ideal coarse proportions for the 10 sites

Index	Method	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 8	Site 9	Site 10	Average
$R$	FCM-global (proposed)	0.9663	0.9161	0.8518	0.8807	0.9127	0.9206	0.9012	0.9297	0.8936	0.9344	0.9107
	LSMM-global	0.9697	0.9243	0.8397	0.8857	0.9130	0.9254	0.9045	0.9299	0.8917	0.9301	0.9114
	FCM-local	0.9673	0.9189	0.8515	0.8778	0.9098	0.9182	0.8992	0.9294	0.8919	0.9338	0.9098
RMSE	FCM-UO	0.1135	0.1671	0.2102	0.1797	0.1736	0.1698	0.1732	0.1613	0.1835	0.1467	0.1679
	LSMM-global	0.1057	0.1590	0.2180	0.1741	0.1725	0.1637	0.1703	0.1600	0.1846	0.1513	0.1659
	FCM-local	0.1122	0.1645	0.2104	0.1816	0.1765	0.1724	0.1750	0.1607	0.1849	0.1474	0.1686
MAE	FCM-global (proposed)	0.0483	0.0652	0.1051	0.0920	0.0865	0.0794	0.0785	0.0696	0.0798	0.0560	0.0760
	LSMM-global	0.0487	0.0598	0.1092	0.0939	0.0878	0.0803	0.0838	0.0727	0.0832	0.0576	0.0777
	FCM-local	0.0467	0.0623	0.1046	0.0934	0.0881	0.0803	0.0791	0.0694	0.0804	0.0560	0.0760

As observed in Table 4, the difference between the ‘LSMM-global’ and ‘FCM-global’ results is small, with a difference of 0.07% in average  $R$ , indicating that the segmentation-then-erosion step in the proposed UO model reduces the errors in the FCM-derived coarse proportions effectively. Additionally, the ‘FCM-local’ method produces accuracy comparable to the ‘FCM-global’ method, since the difference between them is only in the unmixing of the filtered mixed pixels. Overall, despite being an unsupervised approach, the proposed ‘FCM-global’ strategy achieves relatively satisfactory coarse proportions and can contribute to more accurate SPM results.

#### 4.2. Alternatives to segmentation algorithm

To tackle the mixed pixel problem, pixel-based analysis is employed widely in current spectral unmixing and SPM. However, the pre-spectral unmixing process introduces inevitable uncertainties, affecting not only mixed pixels, but also leading to misidentification of pure pixels due to intra-class and inter-class spectral variability issues. This is a common limitation in many existing SPM methods that rely on coarse proportions as a data fidelity term. In this paper, the UO-SPM model incorporates the Otsu-based segmentation method to divide the coarse proportions of each land cover class into targets (more likely to be pure pixels of one class) and backgrounds (more likely to be mixed pixels or pure pixels for other classes). With the goal of minimizing intra-class variance, the Otsu algorithm is appropriate for segmenting the coarse proportions that generally

488 exhibit an obvious two peaks-distributed histogram. Otsu may not be optimal under every circumstance, such  
489 as when the coarse proportion is significantly affected by noise, or when there is a considerable area difference  
490 between the target and background. Nevertheless, it is widely acknowledged that there is no perfect algorithm  
491 that will work with every satellite sensor image (Kotaridis and Lazaridou, 2021). Alternative segmentation  
492 algorithms, such as edge detection and region merging, may demonstrate better performance than Otsu in  
493 specific scenarios. Regarding these methods, it must be noted that the selection of parameters should be done  
494 carefully, as the choice will impact directly on the segmentation output.

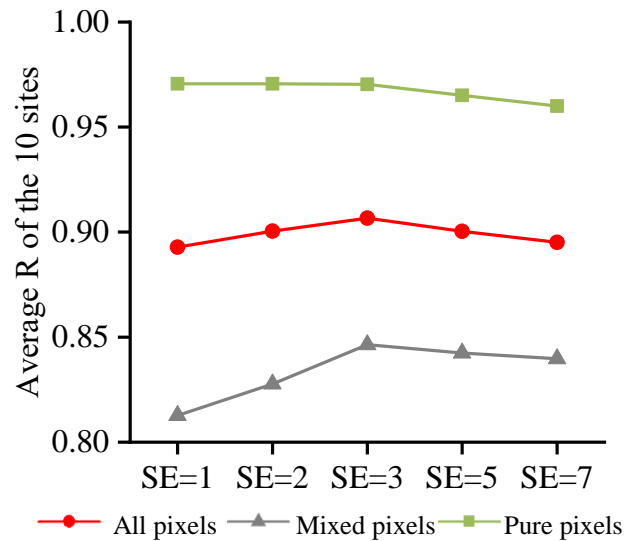
495 In the UO-SPM model, Otsu has the obvious advantage of automatic threshold selection without the need for  
496 parameters or supervision, making it ideal for integration into the proposed unsupervised models. Moreover,  
497 the main goal of employing segmentation is utilization of object-oriented contextual information to  
498 differentiate mixed and pure pixels from the coarse proportions. This enables the exclusion of noisy errors in  
499 the pure pixels while simultaneously obtaining more accurate spectral unmixing for the mixed pixels by  
500 application of a secondary supervised spectral unmixing step. Therefore, the key to UO-SPM is not which  
501 segmentation method is used, but the appropriate use of spatial contextual information through an object-based  
502 analysis, a consideration lacking in conventional pixel-based spectral unmixing and SPM.

#### 504 *4.3. Ideal width of mixed pixel*

505 Ideally, the width of mixed pixels is expected to be one coarse pixel, corresponding to the edge pixels at the  
506 intersection of two land cover objects. In the UO-SPM experiments, the size of the structuring element in the  
507 morphological erosion step was set to three. This decision was made considering the challenges posed by errors  
508 in the pre-spectral unmixing process and uncertainties in the segmentation results, making it difficult to  
509 identify precisely the one-pixel width of mixed pixel positions. If the morphological erosion step is set too  
510 small, it could result in a substantial omission error for the mixed pixels. To investigate the impact of different  
511 sizes of the structuring element in the erosion step, we examined the UO-based spectral unmixing result using  
512 elements with a size of 1, 2, 3, 5 and 7 pixels for the 10 study sites. The average  $R$  values (for the 10 sites) of the

513 UO-derived coarse proportions with different sizes of structuring elements are shown in Fig. 12. It can be seen  
 514 that the average  $R$  values for all pixels and mixed pixels increase initially and then decrease as the size of the  
 515 structuring element increases. Additionally, the  $R$  values for pure pixels tend to decrease when the size of  
 516 structuring element exceeds three. Furthermore, the difference in the average  $R$  values between the results of  
 517 UO with different structuring sizes is less than 1.2% for all pixels. Overall, while the proposed UO model  
 518 requires setting the parameter of the structuring element, it demonstrates satisfactory performance with a  
 519 setting of three, as evaluated across the 10 sites. Hence, a size of 3 pixels for the structuring element is  
 520 suggested for the proposed UO-SPM model.

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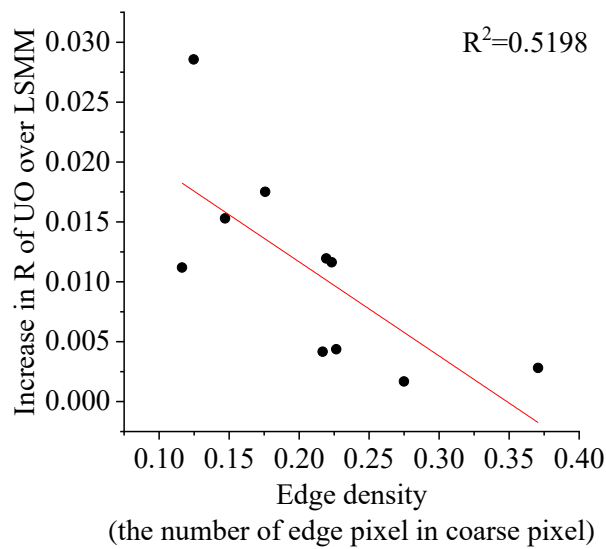
524 Fig. 12. Assessment of the impact of the size of the structuring element (SE) on the UO-derived spectral unmixing results for the 10  
 525 study sites.

526

#### 527 4.4. Limitations of UO-SPM

528 With the object-scale analysis, the proposed UO-SPM model leverages contextual relations that a single  
 529 pixel view lacks. The underlying assumption of UO-SPM is that land cover objects are large-sized, typically  
 530 larger than one coarse pixel (i.e., a H-resolution case) (Atkinson, 2009). For example, in a Landsat image with  
 531 a spatial resolution of 30 m, the proposed UO-SPM requires objects to be larger than 90 m  $\times$  90 m (i.e., 3  $\times$   
 532 Landsat pixels) to identify ideal pure pixels using a structuring size of three for erosion. This makes the method

533 more suitable for homogeneous areas. However, this does not follow that the method is not applicable to  
 534 small-sized land covers, as they may be identified as mixed pixels after the erosion step and then are  
 535 decomposed to obtain coarse proportions. To assess the discrepancies in accuracies between the H-resolution  
 536 and L-resolution cases, the edge density (ED) of the 10 study sites was calculated from the reference land cover  
 537 maps by dividing the total edge length by the total area. Specifically, the number of pixels at the edges is  
 538 viewed as the total edge length, while the total number of pixels is considered as the total area. That is, the unit  
 539 of ED here is the number of edge pixels per pixel. A larger edge density indicates a more complex and  
 540 fragmented landscape (Clément et al., 2017), representing more L-resolution cases in the coarse image, while  
 541 smaller edge density suggests more contiguous patches, representing more H-resolution cases.



543  
 544 Fig. 13. The relationship between the edge density (ED) of the reference land cover images and the increase in  $R$  value of the  
 545 UO-derived coarse proportions compared to the LSMM-derived results for the 10 sites (a larger edge density represents a more  
 546 fragmented landscape, more likely indicating an L-resolution case in the coarse image).

547  
 548 The relationship between ED and the increase in  $R$  of the UO-derived coarse proportions compared to  
 549 LSMM for the 10 sites is shown in Fig. 13. With less fragmented objects (i.e., smaller ED value), the advantage  
 550 of the UO-strategy over LSMM is more evident. This suggests that the proposed method is more suitable for  
 551 the H-resolution case. The reason is that when the size of target object is small, as in the L-resolution case, the

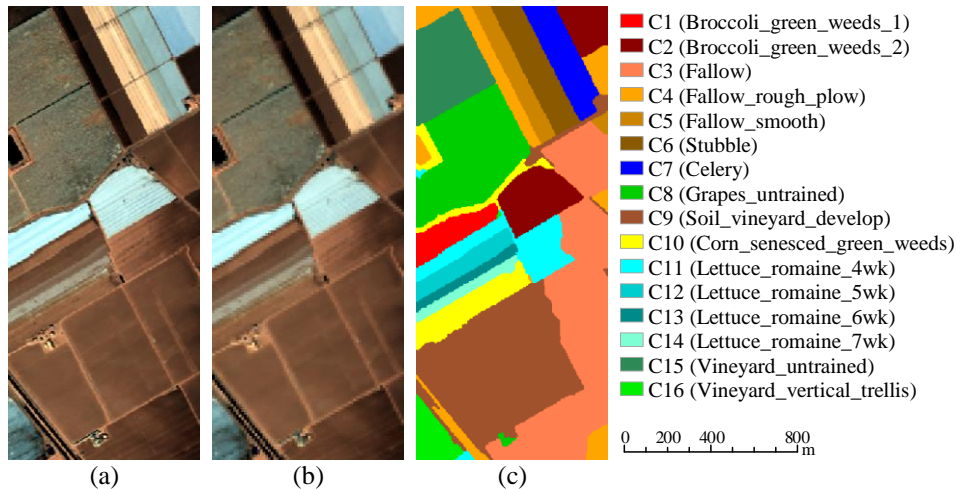


effectiveness of the object-scale analysis diminishes in detecting objects within the coarse pixel, further affecting the performance of spectral unmixing and SPM. Since there is no guidance on predicting the fine land cover distribution within a coarse pixel, for such pixels, if they were correctly segmented as backgrounds by the proposed UO-SPM model for all classes (i.e., remaining mixed pixels), they would be further decomposed in the secondary spectral unmixing step. Conversely, if such pixels were erroneously segmented as pure pixels for one class, the error would propagate into the SPM results. To overcome the challenge of small-sized objects (particularly for those falling entirely within a coarse pixel), the utilization of auxiliary data, such as fine spatial resolution temporally adjacent land cover maps, should be a potential approach. Additionally, to effectively identify objects in Landsat images using UO-SPM, the classification system should be defined at a higher representation level. For example, finding pure pixels for asphalt, concrete and roofing materials within ‘urban areas’ in Landsat images can be challenging. Therefore, it is reasonable to group these materials into a single category, such as an ‘urban’ class, as is commonly adopted in existing global land cover products based on Sentinel-2 and Landsat images (Zhang et al., 2021; Brown et al., 2022). Under such a classification system, regions can be considered relatively homogeneous with significant intra-class variance at the pixel scale. In this scenario, the object-based analysis in UO-SPM offers great advantages compared to pixel-based strategies for addressing such intra-class variance.

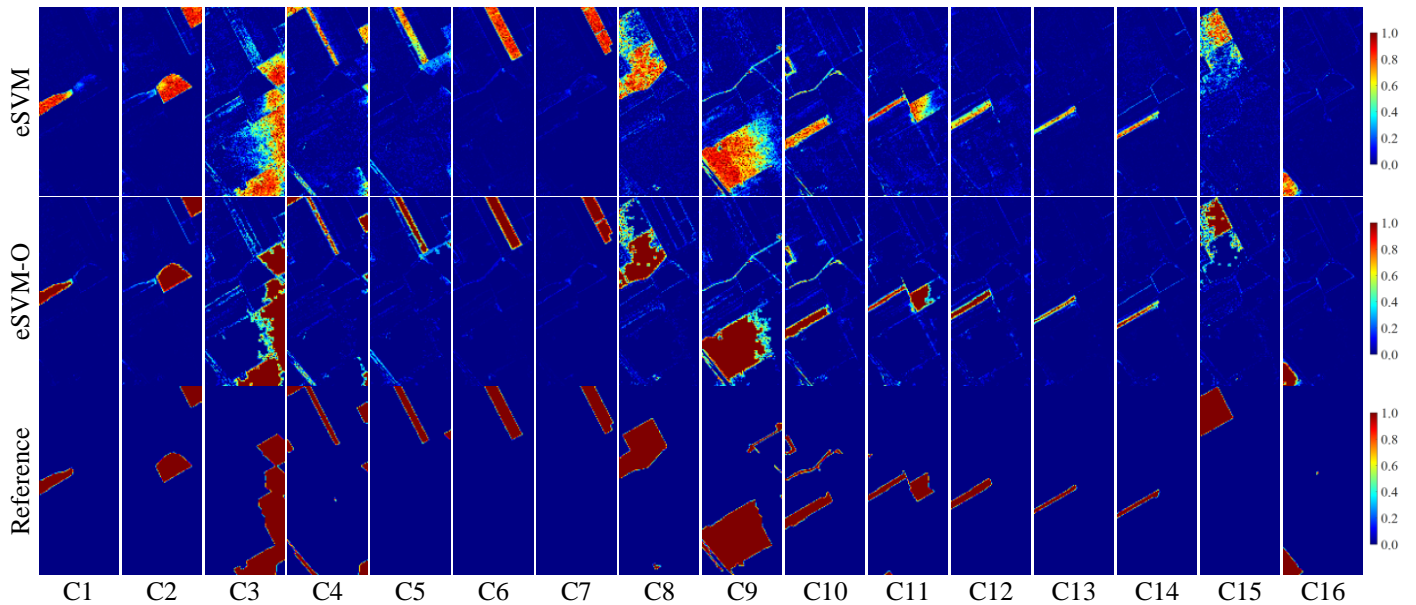
#### *4.5. Applicability to scenes with a large number of classes*

Due to the limited number of spectral bands in multi-spectral images, spectral unmixing methods face inherent challenges in capturing sufficient spectral information to differentiate between a large number of land cover classes. For example, decomposing different types of vegetation, such as trees and shrubs, becomes difficult with only a few spectral bands due to their spectral similarity. Additionally, linear unmixing methods (e.g., LSMM) become more suitable when the number of classes is smaller than the number of bands. In the experiments in Section 3, the proposed UO model was applied to multi-spectral images using a relatively

576 coarse land cover taxonomy with limited spectral bands. When sufficient spectral bands are available to  
 577 differentiate land cover classes, such as hyperspectral images, coarse proportions can be obtained more readily.  
 578



579 Fig. 14. The hyperspectral Salinas AVIRIS dataset with 16 classes. (a) Original 3.7 m image (Bands 90, 65 and 55 as RGB). (b)  
 580 Simulated 11.1 m coarse image obtained by degrading (a) with a scale factor of 3. (c) 3.7 m land cover map produced by Zhao et al.  
 581 (2020).  
 582



583 Fig. 15. Spectral unmixing results for the 11.1 m hyperspectral Salinas AVIRIS dataset.  
 584

585 To evaluate the potential of the proposed object-based analysis in scenes with a large number of land cover  
 586 classes, a hyperspectral image acquired by the Airborne/Visible Infrared Imaging Spectrometer (AVIRIS)

587 sensor was used, as shown in Fig. 14. The image was captured over Salinas Valley in California, USA, and  
588 contains 204 spectral bands (after noise removal) between 0.4 and 2.5  $\mu\text{m}$ , with a spatial resolution of 3.7 m  
589 and spatial size of  $510 \times 210$  pixels. The original 3.7 m hyperspectral image was degraded to 11.1 m to simulate  
590 the coarse image for spectral unmixing, as shown in Fig. 14(b). The 3.7 m land cover map in Fig. 14(c) was  
591 generated by the method developed in Zhao et al. (2020), and has an OA of 99.40% when compared to the  
592 available ground reference data. Similarly, the reference for 11.1 m coarse proportions was produced by  
593 degrading Fig. 14(c) with a scale factor of 3. Here, for spectral unmixing, the unsupervised FCM method was  
594 not considered, as several land cover classes cannot be identified when the number of land cover classes is  
595 large. The proposed UO scheme was also extended to cope with the challenging case in this section.  
596 Specifically, a supervised spectral unmixing method called extended SVM (eSVM) (Li et al., 2015) was  
597 employed to replace FCM in the proposed method. The eSVM decomposes mixed pixels by considering their  
598 proximity to the class cores of pure endmembers, without making hard label decisions. Accordingly, two  
599 supervised spectral unmixing methods were implemented, including eSVM and eSVM-O. For the eSVM  
600 method, we selected randomly 10% of the pure pixels from each land cover class in the reference coarse  
601 proportion images as training samples to predict the remaining pixels. For eSVM-O, the  
602 segmentation-then-erosion step with a structuring size of 3 for erosion was applied to the eSVM-derived  
603 proportions, while the remaining mixed pixels inherited the eSVM-derived proportions directly. Visual  
604 inspection in Fig. 15 shows that compared to the results of eSVM, the eSVM-O reduces the errors noticeably in  
605 the inner regions of objects, and the results are obviously closer to the reference. As listed in Table 5, the  
606 quantitative evaluations based on  $R$ , RMSE and MAE align with the visual comparison. Furthermore, the two  
607 coarse proportions were used as inputs to the SPM methods (including HNN, MRF, PSA and RBF) to generate  
608 the 3.7 m spatial resolution maps. The results are shown in Fig. 16, and the accuracy assessment is provided in  
609 Table 6. It can be seen that the SPM predictions show obvious reduction in errors both visually and  
610 quantitatively when using proportions derived from eSVM-O. Overall, when sufficient spectral bands are  
611 available to distinguish between a large number of land cover classes, such as in hyperspectral images, the

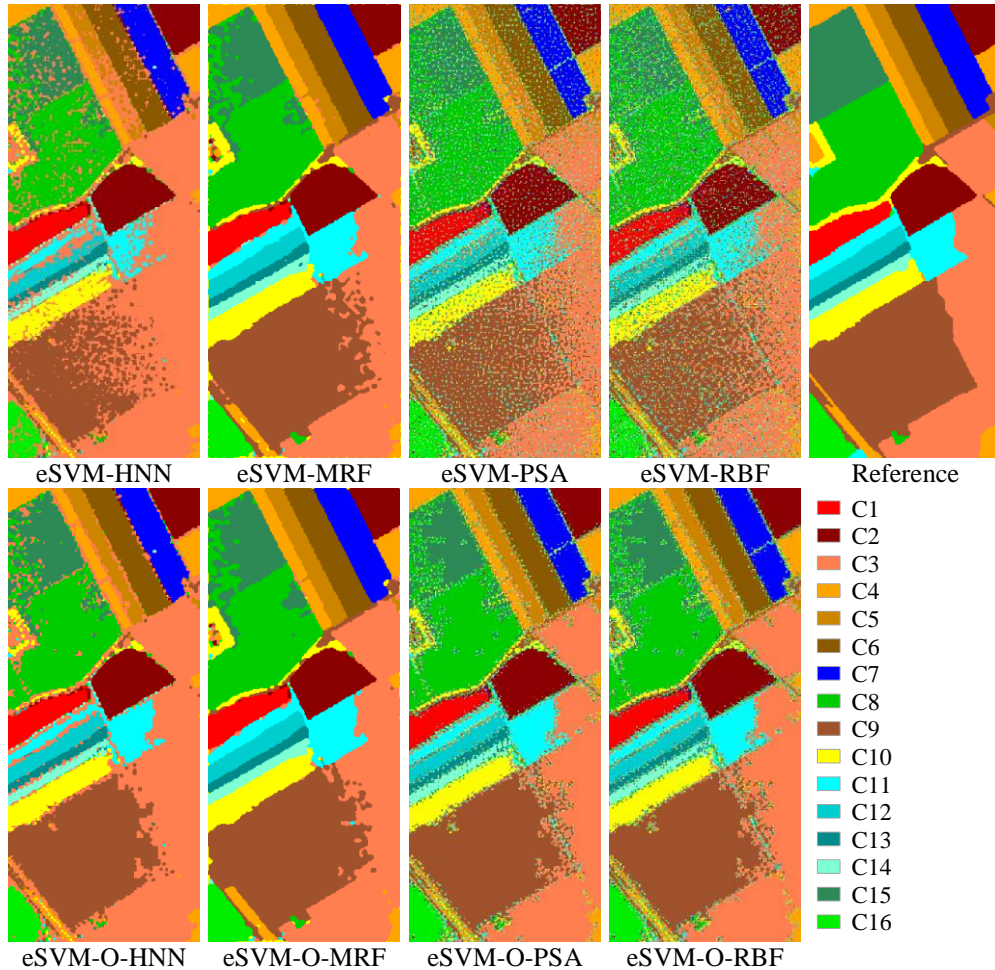
612 object-based analysis proposed in this paper is helpful to further enhance the unmixing results and, eventually,  
 613 to increase the accuracy of SPM predictions.

614  
 615

Table 5 Spectral unmixing accuracies for the hyperspectral Salinas AVIRIS dataset

	<i>R</i>		RMSE		MAE	
	eSVM	eSVM-O	eSVM	eSVM-O	eSVM	eSVM-O
C1	0.9657	0.9705	0.0463	0.0376	0.0109	0.0055
C2	0.9759	0.9800	0.0631	0.0480	0.0199	0.0096
C3	0.8794	0.9236	0.1959	0.1511	0.1115	0.0519
C4	0.8531	0.8560	0.1293	0.1215	0.0462	0.0301
C5	0.8599	0.9094	0.0910	0.0712	0.0343	0.0179
C6	0.9796	0.9794	0.0529	0.0416	0.0160	0.0085
C7	0.9770	0.9774	0.0511	0.0421	0.0131	0.0070
C8	0.8624	0.8945	0.1612	0.1386	0.0725	0.0421
C9	0.9099	0.9340	0.1791	0.1415	0.0960	0.0463
C10	0.8740	0.8811	0.1113	0.1022	0.0410	0.0276
C11	0.8870	0.9146	0.0994	0.0818	0.0387	0.0211
C12	0.9132	0.9456	0.0680	0.0478	0.0245	0.0110
C13	0.9465	0.9493	0.0416	0.0358	0.0110	0.0066
C14	0.9185	0.9266	0.0469	0.0425	0.0139	0.0092
C15	0.8099	0.8507	0.1497	0.1318	0.0605	0.0361
C16	0.9348	0.9385	0.0577	0.0486	0.0147	0.0084
Overall	0.9027	0.9249	0.1088	0.0906	0.0390	0.0212

616



617 Fig.16. SPM results (3.7 m) for the hyperspectral Salinas AVIRIS dataset.

Table 6 OA of SPM results for the hyperspectral Salinas AVIRIS dataset

	HNN	MRF	PSA	RBF
eSVM-SPM	76.60%	91.66%	68.25%	68.36%
eSVM-O-SPM	84.68%	92.03%	82.56%	82.49%

## 5. Conclusion

As a pre-processing step of SPM, spectral unmixing produces coarse proportions, serving as a crucial data fidelity term for various SPM methods, and influencing SPM results greatly. However, widely used pixel-based spectral unmixing methods often introduce inevitable errors due to inherent spectral variability in the observed data. Moreover, pixel-based spectral analysis neglects valuable contextual information on land cover objects, and commonly used supervised-based spectral unmixing methods entail human input, resulting in a heavy labor burden. In this paper, we introduced a fully automatic object-based SPM model, namely UO-SPM, to increase the accuracy of spectral unmixing and ultimately SPM. Given that mixed pixels are often located at the boundaries of land cover classes (i.e., edge of objects), this paper developed an object-scale strategy to identify both mixed and pure pixels. The proposed UO-SPM model was integrated with four SPM methods (i.e., UO-MRF, UO-HNN, UO-PSA and UO-RBF) and evaluated across three multi-spectral datasets. The results were compared with two versions of the existing morphological operation-based SPM method, that is, MFFR-erode and MFFR-open.

The key findings are as follows. Firstly, the proposed UO-SPM model offers an effective solution to reduce errors in spectral unmixing results, subsequently enhancing SPM, with an average increase of 3.65% and 1.09% in  $R$  value for coarse proportions compared to FCM and LSMM, respectively. The UO-SPM strategy produced larger accuracies for SPM than the FCM-SPM and LSMM-SPM methods, with an average increase of 5.89% and 3.04% in OA compared to the FCM-SPM and LSMM-SPM results, respectively. Secondly, evaluation of mixed and pure pixels reveals that both are more accurately classified by the UO-SPM model for all SPM methods. The results include fewer erroneous speckle-like subpixels within pure pixels and produce a more satisfactory fine land cover distribution for mixed pixels. Thirdly, the proposed UO-SPM model is applicable for both SPM methods that comply strictly with the coarse proportions (i.e., RBF and PSA) and methods that do not strictly preserve the coarse proportions (i.e., MRF and HNN). The increase in accuracy is more obvious

643 for UO-PSA and UO-RBF than that for UO-MRF and UO-HNN, while UO-MRF produces the most accurate  
 644 results among all methods. Lastly, the advantage of UO-SPM is more evident for land cover types with  
 645 large-sized objects than for those with small-sized case. With the aim of detecting mixed pixels located at the  
 646 edges of objects, the proposed UO-SPM model is more suitable for the H-resolution case than the L-resolution  
 647 case.

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