A comparison of pixel-based and object-oriented approaches to VHR imagery for mapping saltmarsh plants

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**A R T I C L E   I N F O**

Article history:
Received 3 September 2010
Received in revised form 16 December 2010
Accepted 11 January 2011
Available online 18 January 2011

Keywords:
Saltmarsh
Object-oriented classification
Pixel-based classification
VHR imagery

**A B S T R A C T**

Object-oriented classification (OOC) has shown many significant advantages over other methods for classification of urban or forest ecosystems. However, it remains unclear if this technology could exhibit these advantages on mapping monospecific plant stands in herbaceous plant dominated ecosystems (e.g. saltmarshes). In this study, we compared the effectiveness of OOC and pixel-based classification (PBC) methods for mapping plants in a saltmarsh ecosystem. Quickbird was selected for very high resolution (VHR) imagery. Eleven models defined by classification types, feature spaces, classifiers, and hierarchical approaches with multi-scale segmentation were built for comparison. The results showed that the QuickBird imagery efficiently discriminated saltmarsh monospecific vegetation stands and that OOC performed better than PBC in terms of accuracy. We also found that the improvement of OOC was primarily due to employing membership functions and a hierarchical approach with multi-scale segmentation. Although texture and shape features have been deemed as two major advantages of OOC, enhanced performance was not observed in this study. The results of this study demonstrated that OOC would be superior to PBC for classifying herbaceous plant species in terms of accuracy. To improve the classification accuracy, greater concern should be given to exploration of the relationships between features of both objects and classes and to combining information from different object scales, while shape and texture features can be a minor consideration due to their intricately high spatial variability.

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1. Introduction

Remote sensing offers a practical and economical means to mapping plant distribution over large areas. In recent decades, multi-spectral data such as TM and SPOT have been widely applied in wetlands to identify general vegetation classes or discriminate broad vegetation communities (May et al., 1997; Harvey and Hill, 2001; Ozesmi and Bauer, 2002). However, images from TM or SPOT satellite instruments are insufficient for discriminating vegetation at the species level in herbaceous plant dominated environments (e.g., saltmarshes) due to a lack of high spatial resolution. Specifically, the diameters of plant patches in these habitats may be lower than those covered by the maximum average resolution of SPOT of 10 m and TM of 30 m, resulting in the formation of mixed pixels containing several plant species (Adam et al., 2010; He et al., 2010). Although the linear spectral mixture analysis (LSMA) (e.g., Shimabukuro and Smith, 1991) model has been proposed to enhance coarse image classification, this method can only produce the proportions of multiple materials of each pixel (or objects) rather than the actual distributions of target species. Therefore, a fine sensor with a resolution of several meters is required to precisely map vegetation stands of a single species (Robert, 1996). Airborne imaging spectroscopy, which was the only very high resolution (VHR) remote sensor available before the 21st century, has been successfully used for detection of monospecific vegetation stands in various ecosystems including coastal areas (e.g. Thomson et al., 2003; Thomson et al., 2004; Yang and Everitt, 2010), due to its advantages such as that several instruments can be mounted simultaneously with selected bands and that the fly height, direction and time can be adjusted to obtain optimal images. However, airborne systems are rarely provided for many ecosystems because of their unfixed orbits, great expenses, low frequency of surveying (Wulder et al., 2004; Adam et al., 2010). Fortunately, the recently launched VHR satellite sensors, such as QuickBird and IKONOS, have achieved high spatial resolution similar to airborne imagery and are also available over a range of spatial, spectral, and temporal scales and thus provide new opportunities to monitor herbaceous plant dominated ecosystems.

It is easy to understand that finer spatial resolutions result in more detailed imagery, but it is also worth noting that land use/land cover classification accuracy may decrease due to the increased intra-class variability inherent from more detailed and higher spatial resolution data (Su et al., 2004). Traditional supervised/unsupervised classifications and sub-pixel analysis were originally designed for pixel-based techniques, which are not suitable for processing of VHR images due...
to a lack of spatial concept (Blaschke et al., 2000; Blaschke and Strobl, 2001). As the spatial resolution of remote sensing data increases, the so-called "salt-and-pepper" problem of pixel-based classification (PBC) becomes more serious. This limitation has facilitated the emergence of object oriented classification (OOC) when analyzing VHR images. OOC classifies contiguous homogeneous regions or image objects rather than single pixels by exploiting information (shape, texture and contextual information) hidden in spectra (Yoon et al., 2005). Therefore, OOC is expected to extract real world objects with not only high classification accuracy but also proper shape, which is difficult to accomplish using common PBC (Baatz et al., 2004). As the concept rose in the 1970s, the idea of OOC was far from novel (de Kok et al., 1999), but earlier attempts of OOC did not produce satisfying results because of limitations in computer hardware/software, image resolution, and interpretation theories (Flanders et al., 2003). Since the mid-1990s, the demand for object-oriented techniques has been stimulated along with the development of computer technology and the availability of high resolution imagery (de Kok et al., 1999; Blaschke and Strobl, 2001).

Numerous empirical studies published in peer-reviewed journals have provided sufficient evidence of the advantages of OOC over PBC (e.g., de Kok et al., 1999; Blaschke and Strobl, 2001). However, most of these studies have focused on classifying urban ecosystems with regular shapes and apparent profiles, and on arid/sub-arid forest ecosystems in which vegetation plants occur in large extension and single trees grow in large stands. Recently, sporadic applications employing OOC have focused on herbaceous plant dominated ecosystems (e.g., Cao et al., 2007; Jobin et al., 2008); however, these studies have seldom challenged the discrimination between monospecific vegetation stands. To the best of our knowledge, no significant research has been conducted to evaluate the use of OOC in saltmarshes to map monospecific vegetation stands, and accordingly to examine the possible advantages of this technique. It is worthwhile to monitor monospecific vegetation stands in saltmarshes because they are not as easily detected as terrestrial plants due to short ecotones and narrow vegetation units and irregular shapes of plant patches (Adam et al., 2010). Moreover, the saltmarshes tend to form monoculture and zonal pattern (Chapman, 1974), which presents a good opportunity to identify the plant at species level via vegetation covers monitoring.

According to previously published studies (e.g., Baatz and Schäpe, 1999; Wang et al., 2007; Platt and Rapoza, 2008), at least three factors, texture and shape, membership function, and hierarchical approach with multi-scale segmentation, are important for improving the accuracy and efficiency of OOC. In this study, we conducted a detailed comparison of PBC and OOC for the use of mapping an invasive plant with multi-scale segmentation, are important for improving the texture and shape, membership function, and hierarchical approach (1999; Wang et al., 2007; Platt and Rapoza, 2008), at least three factors, good opportunity to identify the plant at species level via vegetation patches (Adam et al., 2010). Moreover, the saltmarshes tend to form monoculture and zonal pattern (Chapman, 1974), which presents a good opportunity to identify the plant at species level via vegetation covers monitoring.

2. Study area and data

2.1. Study area

The study area (Fig. 1) is part of the Yangtze River Estuary, which typically consists of marshy land. The tidal fluctuations of the Yangtze River Estuary are regular and semi-diurnal and consist of two distinctive periods of ebb and flood tides during a day. The area is located at a high intertidal zone and is only affected by spring tide. The dominant vegetation of the upper saltmarsh includes Phragmites australis (hereafter referred to as Phragmites) and Spartina alterniflora (hereafter referred to as Spartina). Spartina was introduced into the area in 2001 for land reclamation owing to its capacity to increase sediment accretion (Chen et al., 2004). A rapid succession occurred after several years of its burst growth and expansion (Zhao et al., 2009), and its invasion has threatened the native ecosystems and coastal aquaculture (Chen et al., 2004). Although the native species Phragmites is rapidly being replaced by Spartina, it still dominates the higher intertidal zone and coexists with Spartina. Both plants grow in large stands and form pure stands, making them ideal candidates that could be detected from remote sensing imagery, but their dense populations, vague profile, overlapped phenophase and similar spectral character make it difficult to distinguish them.

2.2. Image data and pre-processing

A Quickbird imagery acquired on 10 May 2006 was used in the study. The data were delivered as a Standard Imagery Bundle (GeoTIFF format) including one panchromatic band (450–900 nm) and four multispectral bands: blue (450–520 nm), green (520–600 nm), red (630–690 nm), and near-infrared (NIR) (760–900 nm). Prior to delivery, the imagery was radiometrically and geometrically corrected and rectified to the world geodetic survey 1984 datum (WGS84) and the universal transverse Mercator (UTM) coordinate system. A sharpened image (spatial resolution = 0.61 m) was initially developed by merging the high resolution pan image (0.61 m) with the low resolution multi-spectral image (2.4 m), after which a subset of the study area was cut for the following processes. All procedures for image merging and cutting were conducted using ERDAS IMAGINE 9.2 (ERDAS, Inc., Atlanta, GA, USA).

2.3. Field investigation

The reference data used for classification were collected at random between April and November in 2006. When the field investigation was performed, a portable Global Position System (GPS) was used to locate the target ground objects such as plant patches, mudflats, pools and tidal creeks. To help localization, geo-referenced color maps of QuickBird images were printed beforehand and then taken with the investigators for field checks. Some target objects were easily localized and identified in terms of distinctive ground objects such as embayments of tidal creeks, cross points of roads and dikes, and temporary construction projects. Field notes made on the images were then taken to the laboratory for further classification and accuracy assessment.

Phenological observation of Spartina and Phragmites was conducted from 2005 to 2006, and simple phenological phases were determined (Table 1). Our field observations revealed that the phenophases of Phragmites and Spartina were somewhat different. Phragmites begins to germinate in early April, undergoes a rapid growth stage from June to mid-August, flowers in mid-October, and senesces in late November. Conversely, Spartina emerges in May, undergoes rapid vegetative growth from June to early September, flowers in late September, and dies in late December (He et al., 2010; Yan et al., 2010). These differences in phenophase provide a potential to discriminate the species using remote sensing technology. The QuickBird imagery was acquired in early May 2006 when Spartina and Phragmites were distinguishable due to being in different phenological phases, and our field spectral measurement confirmed their distinguishable spectral characteristics during that period (Fig. 2).

3. Image classification

The image was classified into three types: Phragmites, Spartina, and non-vegetation. A total of eleven image classification models (Table 2) were constructed to evaluate the performance of OOC and PBC, by categorizing them into two broad groups (i.e., OOC models and PBC models). The models were not arbitrarily selected, but constructed under serious consideration for multiple comparisons (longitudinal, crosswise and general comparison). The longitudinal comparison only...
compares the model pairs with different classification types (OOC vs. PBC), and the crosswise one compares the model pairs with the same classification type but with another different key aspects, such as classifier, feature space, or hierarchical approach with multi-scale segmentation (Table 2), while the general one compared overall performance when the compared models have more than two different aspects. The whole process for models construction is illustrated in Fig. 3. Traditional PBC classification models (modes #9 and #10) were conducted using ERDAS IMAGINE 9.2, while others were conducted using eCognition Professional 4.0 (Definiens, Inc. Germany, hereafter eCognition) with fuzzy classification integrated.

### 3.1. Image segmentation

OOC is based on composite image objects, so the first procedure (image segmentation) subdivided imagery into separated regions (Fig. 4). The segmentation algorithm used is a bottom up region-merging algorithm that begins with one-pixel objects. The procedure includes a pair-wise clustering process to merge smaller objects into larger ones with uniform texture and color, as well as an optimization process to simultaneously ensure that among all of its neighbors, and an object is merged with the one that produces a minimal increase of spatial and spectral heterogeneity defined by a set of parameters, such as scale, color, and shape. When the spectral and spatial heterogeneity of one object reaches a defined threshold, the procedure stops its growth.

The size of an image object is determined by a scale parameter (a dimensionless integer). The larger the scale parameter, the more objects can be fused and the larger the objects grow (Benz et al., 2004). Two other parameters, smoothness and compactness, determine how much the smoothness and compactness contribute to the shape heterogeneity. Due to the incorporated shape parameters, the

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**Table 1**

<table>
<thead>
<tr>
<th>Phenological phase</th>
<th>Phragmites</th>
<th>Spartina</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germinate</td>
<td>Early–April</td>
<td>May</td>
</tr>
<tr>
<td>Rapid growth stage</td>
<td>June–Mid August</td>
<td>June–Early September</td>
</tr>
<tr>
<td>Flower</td>
<td>Mid October</td>
<td>Mid–August</td>
</tr>
<tr>
<td>Senesce</td>
<td>Late November</td>
<td>Late–December</td>
</tr>
</tbody>
</table>
algorithm avoids branched segments or image objects with a fractally shaped borderline (Baatz et al., 2004).

Although image segmentation is very important to OOC, there are no established criteria or sophisticated experiences to determine the best parameters for segmentation. Therefore, we employed a qualitative visual inspection method as many other researchers have done (Chen et al., 2006). To identify a better scale by comparing segmented objects with uniform visual properties of the imagery, different groups of possible parameters were tested. Once the scale parameter was determined, the other parameters were iteratively modified to refine the shape of the objects. The target level of segmentation for all object-oriented models was determined by the following parameters — scale: 35, color: 0.7, shape: 0.3, smoothness: 0.5, and compactness: 0.5. In model #11, a lower level of segmentation was added for multi-scale and hierarchical analysis, and its segmentation parameters were: scale: 15, color: 0.7, shape: 0.3, smoothness: 0.5, and compactness: 0.5. For pixel-based models performed in eCognition, the image was segmented into single pixels by a specified scale parameter of 0.

3.2. Classifiers

Performances of different classifiers were explored to test how knowledge-based membership functions can influence OOC. ISODATA algorithm, the most frequently and widely used unsupervised classifier, was adopted in model #9 to test the traditional supervised PBC. The imagery was initially classified into 30 classes with maximum iterations of 15 and a convergence threshold of 0.95, after which it was coded into three classes: Phragmites, Spartina, and non-vegetation. Maximum likelihood, which is the most accurate and frequently used supervised PBC method (Wong et al., 2005), was adopted in model #10. The nearest neighbor classifier was also adopted to conduct supervised classification in models #1, #2, #3, and #4. The nearest neighbor classifies each image object to the class which has the sample object closest to it in a given feature space (Baatz et al., 2004). In all supervised models, 10 classes were identified first and then recoded into the three classes. Training patches for all supervised models were selected from field investigation and remained the same.

Another classifier employed in the study is the membership function. Unlike the former three classifiers who directly calculate a membership of each object or pixel in a predefined multidimensional feature space, a single membership function can only calculate membership of objects or pixels in one dimension. To cover multidimensional feature space, multi membership functions have to be combined logically, but on the other hand, the membership function is more feasible to include expert knowledge. For example, we found that water bodies in the image typically have a low value on the infrared band. Knowing this, a membership function can be constructed to assign each object a value between zero and one depending on its infrared ratio, which is the ratio of the infrared value to the sum of blue, green, red and infrared (Fig. 5). Because its great ability to incorporate expert knowledge, it was convinced to help improve OOC accuracy in many studies (Cao et al., 2007; Platt and Rapoza, 2008). Typically, traditional PBC does not employ membership functions, whereas OOC allows objects to be classified using rules related to spectrum, shape, texture, or context. In order to test if membership functions can show some advantages here, models depending on membership functions with or without employing nearest neighbor classifier of both PBC and OOC type were compared (Table 2).

3.3. Feature space

Different feature spaces were explored to test the influence of texture and shape features on classification. Typically (especially in PBC), image classification employs standard feature space (SFS) comprising of blue, green, red, and near infrared bands. Nevertheless, classification sometimes also takes advantage of other features rather than standard spectral features. This is especially important for OOC, as objects represent more features than pixels. Features of objects include spectrum, shape, texture, and context, while features of pixels are limited to spectrum and texture. To evaluate the effect of shape and texture features on classification, optimized feature space (OFS) and SFS were compared. The optimized features were obtained from the feature space optimization procedure of eCognition, which calculates a subset of feature space with the greatest separate distance at a given dimension (Baatz et al., 2004). Because the procedure fits a statistical model based on training samples, the model may fit the training data much better than the validation data, i.e. over-fitted problem (Platt and Rapoza, 2008). To minimize this problem, feature bands with non-normalized units, such as length or area, were excluded. The optimized feature spaces of both OOC and PBC models are listed in Table 3. Five feature bands were selected as the dimension of optimized feature spaces because our tests showed that an increased number of feature bands (>5)

![Fig. 2. Field reflectance spectra of Spartina and Phragmites acquired in early May. The straight lines above the spectral curves show the location and width of multi-spectral bands of Quickbird sensor (the upper long line stands for the pan band and the lower four short lines stand for the blue, green, red and infra-red band from left to right respectively).](image-url)
did not increase the classification accuracy. The textural bands calculated from gray level co-occurrence matrix (GLCM) in the optimized feature spaces were computed according to Haralick et al. (1973).

Another feature space was also explored to test the effects of texture and shape features. When membership functions were employed, a selected feature space based on our knowledge that derived from field measurement and exploring of the image was defined. We called this feature space knowledge-based feature space (KFS), and it consisted of features used to define every single membership function. It should be noted that the features in our final KFS were all related to spectral features (Table 4), although we had explored other features before determining the ultimate strategy of the membership function definition. A convicive example is, we paid great attention to texture and shape features, especially those included in the aforementioned optimized feature spaces, but few tests showed improved classification.

3.4. Hierarchical analysis

The multi-scale segmentation procedure of eCognition enables users to make a netted hierarchical analysis and is exclusively of OOC. In a hierarchical analysis and multi-scale environment, information regarding image objects on the smaller scale is used to correct and optimize the classification results of the larger scale, and the information describing image objects in the larger scale is used to understand the image in the smaller scale. Thus, the hierarchical approach with multi-scale segmentation should have the ability to enhance OOC. A hierarchical approach was incorporated into model #11 to evaluate its effect on OOC, with the multi-
scale segmentation being introduced in the segmentation section. The hierarchical structure of model #11 is illustrated in Fig. 6. In the inheritance hierarchy, class descriptions (in our case, membership functions) defined in parent classes are inherited by child classes. The group hierarchy combines sub classes to a superior semantic class, but the super class does not pass down its class descriptions. The structure hierarchy is slightly different from the former two. Though it most often has parallels to the group hierarchy, its main function is used to fusion continuous objects (even from different segmentation levels) in the same structure group.

3.5. Classification evaluation

To evaluate the classification accuracy of the models, error matrices were established to make a comparison between predicted classes and actual classes. Because our study area is relatively small and the three targeted classes are readily distinguished visually during early summer or mid-autumn, a subset that occupies half of the area of the image was interpreted manually to stand for actual classes and the classification evaluation was based on the interpreted subset. That is, the class attributes of points on the manually interpreted image were compared to those on the classified image for each model. Thus, a total of eleven matrices were established, and in each error matrix the overall accuracy, producer's accuracy, user's accuracy, errors of commission, and errors of omission were included. Table 5 lists the kappa coefficient and overall accuracy in the above analysis.

4. Results and discussion

The overall accuracy of all models ranged from 78% to 87%, with a kappa coefficient that ranged from 0.64 to 0.76 (Table 5). Except for model #10, all other models obtained an overall accuracy greater than 80%. The OOC model #11 reached an overall accuracy of 87% and a kappa coefficient of 0.76, which was the highest among all models. The most accurate PBC models were supervised models #3 and #9, which had the same overall accuracy (82%) and kappa coefficient (0.67), which was significantly lower than that of model #11. Although there is no established standard for accuracy assessment, a commonly recommended accuracy is 85% (Foody, 2002). According to the guidelines regarding accuracy, only two OOC models (models #6 and #11) met the target, but the PBC model did not. Additionally, Fig. 7 shows that an OOC model significantly reduced the salt and pepper effect when compared to the PBC models (models #3 and #9). In this case, OOC was superior to PBC for extracting ground objects, showing more accuracy in classification and more perceivable in shapes. These results are consistent with those other studies concerning the comparison between OOC and PBC (e.g., An et al., 2007; Radoux and Defourny, 2007; Im et al., 2008).

4.1. Texture and shape features

Before considering the effect of texture and shape features, a longitudinal comparison was made between models #2 and #1 to evaluate the OOC model, i.e. excluding OFS, membership function, and the hierarchical approach that may introduce shape and texture
features. Both models omitted membership functions and adopted the nearest neighbor (NN) classifier and standard feature space (SFS). Their proximate accuracy (Table 5) suggested that use of the base OOC model without employing texture and shape features cannot get higher accuracy than PBC.

Two model pairs (models #1 vs. #3 and models #2 vs. #4) were compared crosswise to estimate the effect of textural features. Models #2 and #1 used spectral features alone, while models #4 and #3 used optimized feature spaces including textural features (Table 3). Apparently, the textural features benefited neither OOC nor PBC.

OOC models #4 and #2 had an overall accuracy of 80% and 81%, respectively, and the same kappa coefficient (0.65). Similarly, PBC models #3 and #1 had an overall accuracy of 82% and 81%, respectively, and the same kappa coefficient (0.67), which was slightly higher than the OOC models. To evaluate the effect of shape features on OOC and further evaluate texture features on OOC, models #4 and #6 were explored. Contrary to our expectation, shape features were excluded from the OFS of model #4. Because the feature space optimization procedure was only applied to training samples, the exclusion of shape features in OFS might imply that there were no well-distinguishable shape features between objects of different classes in the training data. Nevertheless, model #6 added more evidence to the inefficiency of shape features, as membership functions of model #6 considered the entire image space. After checking all features according to our prior knowledge and exploration of the imagery, the features selected that define the KFS of model #6 (Table 4) were all related to spectra rather than shape or texture because Phragmites and Spartina have fairly uniform textures and uniformly irregular shapes. Therefore, the merit of membership function based on shape or texture feature was not displayed in our case. These findings are different from those of other studies conducted in urban areas or forest ecosystems (e.g., Platt and Rapoza, 2008; Su et al., 2008), where OOC could significantly increase the accuracy by employing shape or textural features.

To explain these results, we may have to examine the different characteristics of various ecosystems. Generally, the land use types in urban and suburban areas, such as roads, buildings and public squares show similar spectra (the false “different objects same image” phenomenon), leading to false classification and low accuracy of PBC. Conversely, distinctive spatial features such as textures, shapes, and schematics can be exploited from the geometry and heterogeneity of urban and suburban land use types (Cleve et al., 2008), and thus OOC can acquire more accurate classification. In forest ecosystems, although vegetation patches may show irregular shapes, the same vegetation type tends to form a uniform and distinct texture on VHR imagery because of the large stands of single trees (the stands of single trees are larger than the resolution of VHR images, forming coarser images with apparent textures). However, in saltmarshes, herbaceous vegetation exhibits high spatial variability because of short ecotones and narrow vegetation units produced by steep environmental gradients; therefore, it is often difficult to identify unambiguous boundaries and uniform shapes of vegetation types (Schmidt and Skidmore, 2003; Adam et al., 2010). Moreover, these morphological similarities between saltmarsh plants usually cause them to have similar textures in present VHR imagery. Those characteristics, which indicate irregular and changeable shapes of vegetation patches, similar textures amongst vegetation patches, and

Table 3
Feature bands composition of the optimized feature space at object/pixel level.

<table>
<thead>
<tr>
<th>Classification level</th>
<th>Features</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Object</td>
<td>Ratio of band 3 (red)</td>
<td>The ratio between band 3 and the sum of 4 multi-standard bands</td>
</tr>
<tr>
<td></td>
<td>GLCM matrix correlation at 45° direction of all bands</td>
<td>The local homogeneity of all bands</td>
</tr>
<tr>
<td></td>
<td>GLCM matrix entropy at all direction of all bands</td>
<td>Whether pixels have similar brightness values of all bands</td>
</tr>
<tr>
<td></td>
<td>GLCM: Mean at 45° direction of band 2 (green)</td>
<td>The mean frequency of co-occurrence pair pixels in blue band</td>
</tr>
<tr>
<td></td>
<td>GLCM: Standard deviation at 90° direction of all bands</td>
<td>The dispersion of values around the mean</td>
</tr>
<tr>
<td></td>
<td>Mean value of band 2 (Green)</td>
<td>The brightness of the green band</td>
</tr>
<tr>
<td></td>
<td>GLCM: Correlation at all direction of band 2 (green)</td>
<td>The local homogeneity of green band</td>
</tr>
<tr>
<td></td>
<td>Mean value of band 3 (red)</td>
<td>The brightness of the red band</td>
</tr>
<tr>
<td></td>
<td>Mean value of band 4 (near infrared)</td>
<td>The brightness of the near infrared band</td>
</tr>
<tr>
<td></td>
<td>GLCM: Standard deviation at 90° direction of all bands</td>
<td>The dispersion of values around the mean by all bands</td>
</tr>
</tbody>
</table>

GLCM: gray level co-occurrence matrix.

Table 4
Features used to define membership functions. The features are used in all models that incorporated membership functions.

<table>
<thead>
<tr>
<th>Classes</th>
<th>Features used to assign membership of objects to classes</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phragmites</td>
<td>Ratio of band 4 (infrared)</td>
<td>The ratio between band 4 and the sum of 4 multi-standard bands</td>
</tr>
<tr>
<td></td>
<td>Mean value of band 4 (infrared)</td>
<td>Inverting the inheritance from other classes</td>
</tr>
<tr>
<td>Spartina</td>
<td>Ratio of band 4 (infrared)</td>
<td>The ratio between band 4 and the sum of 4 multi-standard bands</td>
</tr>
<tr>
<td></td>
<td>Mean value of band 4 (infrared)</td>
<td>The brightness of the infrared band</td>
</tr>
<tr>
<td>Non-vegetation</td>
<td>Ratio of band 4 (Infrared)</td>
<td>The ratio between band 4 and the sum of 4 multi-standard bands</td>
</tr>
</tbody>
</table>
blurred boundaries between adjacent plants, tend to make the rich spatial information of VHR images in saltmarshes useless. However, in the present study, the distinguishable spectra produced by phenology helped discriminate different plants. Although the canopy densities of the two plants differed somewhat, the resolution of the QuickBird sensor was still too coarse to capture this information in terms of texture. Therefore, it is not surprising that texture and shape features did not influence the classification accuracy in the present study.

4.2. Membership function

To examine the effect of membership functions on classification, we first crosswise compared two model pairs (PBC models #1 vs. #7, and OOC models #2 vs. #8). Within each pair, the only difference was whether the membership function was employed or not (Table 2). Specifically, models #7 and #8 employed the membership function, while models #1 and #2 did not. The results showed that, models #7 and #8 did not produce higher accuracy than models #1 and #2, respectively. The comparisons showed that membership functions could not improve the performance of OOC and PBC when employing NN classifiers. However, this does not mean that the membership function is inefficient. The membership function and the NN classifier calculate their own probabilities, and the lower probabilities tend to be selected as the actual probability of each object belonging to a class when they are integrated. Thus, they may undermine the performance of each other. PBC model #5 and OOC model #6 employed the membership function but did not integrate the NN classifier. As a result, model #6 acquired a high overall accuracy of 85% and a kappa coefficient of 0.74, which was significantly higher than those of models #2, #4 and #8, while model #5 did not improve the accuracy when compared to other PBC models. These results showed that membership functions helped improve the performance of OOC, but not PBC. At the pixel level, the feature value of a single pixel is extracted to define the membership function. Instead, on the object level, the feature value of an object is the average of all included pixels. As the derived average values have smaller variance than their original values, the heterogeneity of the image on the pixel level should be larger than on the object level. This may make the membership function more capable of distinguishing objects than pixels, and therefore explain the advantages of membership functions in OOC.

4.3. Hierarchical approach with multi-scale segmentation

A hierarchical approach with multi-scale segmentation is only the property of OOC models. In our case, OOC model #11 was constructed by adding a hierarchical analysis with multi-scale segmentation to model #7, which was the highest OOC model without employing multi-scale analysis. The results showed that, by combining information on both the upper scale (scale parameter: 35) and the lower scale (scale parameter: 15), model #11 produced the highest accuracy among all models, increasing 2% in both kappa coefficient and overall accuracy more than model #7. This 2% increase was small, but significant. In our study area, most objects of the three target classes could be easily recognized at the upper scale (the main classification scale). At this scale, most objects could be correctly classified, except for some small patches that needed to be recognized and rectified from the lower scale. As those small patches occupied a small part of the total area, it is not likely that they contributed much to the final performance of classification, even though they were all correctly defined, adjusted, and classified. Generally, OOC has the ability to discriminate different classes appropriately in one proper scale, but it may not detect information at smaller scales. Scale can be regarded as the magnitude or level of abstraction on which a certain phenomenon

### Table 5

<table>
<thead>
<tr>
<th>Model</th>
<th>Kappa</th>
<th>Overall accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.67</td>
<td>81%</td>
</tr>
<tr>
<td>2</td>
<td>0.65</td>
<td>81%</td>
</tr>
<tr>
<td>3</td>
<td>0.67</td>
<td>82%</td>
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is described (Baatz et al., 2004). The segmentation scale of objects determines how detailed information can be derived by OOC. The introduction of the hierarchical approach and multi-scale image segmentation helps derive and combine information at different scales from as large as the extent of an image to as small as the resolution of one pixel. Moreover, in a hierarchical approach, context features can be explored fully. Thus, it is feasible that OOC applying a hierarchical approach with multi-scale segmentation can acquire more accurate results than OOC based on a single scale. Our results confirmed the contribution of this point.

4.4. The general comparison between PBC and OOC

The most accurate OOC model (model #11) was compared with the most accurate PBC one (model #9) to evaluate their general performance. OOC obtained a higher accuracy than PBC (87% vs. 82%), as well as lacked the “salt and pepper”. However, reducing the “salt and pepper” does not always perform advantageously. Fig. 8 explains that the “salt and pepper” has both advantages and disadvantages. In PBC, very small patches and pixels different from their neighbors would represent as “salt and pepper”, and they may be classified correctly or mistakenly. Those correctly classified “salt and pepper” would be useful for invasive plant monitoring, as invasive plants like Spartina usually colonize beginning with very small patches and then spread out. OOC reduces the “salt and pepper” by merging pixels into objects, and small objects into large objects, but it may lose some important detail information. A multi-scale analysis can overcome this problem in some extent by integrating information from smaller scales. This undoubtedly adds another highlight to multi-scale analysis.

5. Conclusions

In our study area, the QuickBird imagery was sufficient to monitor the monospecific stands of saltmarsh plants with both OOC and PBC. This type of mapped data derived from QuickBird images with OOC would be useful for invasive plant control, ecological conservation, etc.

Membership function and hierarchical approach with multi-scale segmentation were important factors to improve OOC accuracy, while textural and shape features did not improve OOC. Although membership function is not exclusive to OOC, PBC did not benefit from it in this study. It is reasonable to assume that the membership function should be more broadly applicable in OOC because the commonly used variables of membership function, such as shape and context, are only meaningful for objects. A hierarchical approach with only two level segmentations was used in the study. Because the hierarchical approach has the ability to combine information from various scales, a more complicated and nested hierarchical structure may be expected to further refine OOC. Shape and textural features should be the important aspects to improve OOC, but they did not show any superiority in our test. This was likely because no target class contained uniform shape features or distinct textural features that were more distinguishable than spectral features. The rich spatial information contained in VHR images must be regular and distinguishable between objects of different classes, so that it can help improve OOC.
Our results demonstrate that OOC could still be superior to PBC for classifying monospecific stands of herbaceous plants in terms of accuracy, though the reducing "salt and pepper" is hardly advantageous. To improve the accuracy, a priority may be gained by fully exploring the relationships between features of objects and classes, and combining information from different object scales. Conversely, shape and texture features may be a minor consideration because of their complication caused by high spatial variability.

Acknowledgements

This study was supported by a grant from the National Natural Science Foundation of China (grant no. 2010CB950602) and the National Natural Science Foundation of China (grant nos. 30870409 and 40471087), and the Science and Technology Commission of Shanghai (no. 10dz1200603). Before the submission, we have employed an international scientific editing service (http://www.internationalscienceediting.cn/) to correct the potential linguistic problems in the manuscript, and we appreciate the professional service from the editor.

References
