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Mapping of Freshwater Lake Wetlands Using Object-Relations and Rule-based Inference

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Abstract: Inland freshwater lake wetlands play an important role in regional ecological balance. Hongze Lake is the fourth biggest freshwater lake in China. In the past three decades, there has been significant loss of freshwater wetlands within the lake and at the mouths of neighboring rivers, due to disturbance, primarily from human activities. The main purpose of this paper was to explore a practical technology for differentiating wetlands effectively from upland types in close proximity to them. In the paper, an integrated method, which combined per-pixel and per-field classification, was used for mapping wetlands of Hongze Lake and their neighboring upland types. Firstly, Landsat ETM+ imagery was segmented and classified by using spectral and textural features. Secondly, ETM+ spectral bands, textural features derived from ETM+ Pan imagery, relative relations between neighboring classes, shape features, and elevation were used in a decision tree classification. Thirdly, per-pixel classification results from the decision tree classifier were improved by using classification results from object-oriented classification as a context. The results show that the technology has not only overcome the salt-and-pepper effect commonly observed in the past studies, but also has improved the accuracy of identification by nearly 5%.
Keywords: rule-based inferring; object-based classification; freshwater lake wetland; relation feature; Hongze Lake

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1 Introduction

Freshwater lake wetlands play a key role of social, economic and cultural importance not only at a local scale, but also at a global scale (Podolsky and Conkling, 1991; Harvey and Hill, 2001). They constitute essential links of the hydrological and biogeochemical cycles, and influence many aspects of ecology, economy, and human welfare (Lehner and Döll, 2004). Fresh wetlands support a unique habitat for a great variety of hydrophytic plants, fish, and wildlife (Töyrä *et al.*, 2001). They improve water quality, recharge groundwater and control floods. However, over the past three decades, freshwater lake wetlands have been greatly lost in China due to development, filling, reclamation, or damaged due to the changes of surrounding upland. Some of wetlands, especially those near lakes, have been reclaimed for economic activities such as rice farming and fish-raising. Some wetland functions have been damaged by network fishing. Some wetlands are damaged by periodical lack of water. Therefore it is becoming increasingly important to identify and inventory the extent and condition of present freshwater wetlands. The information on the quantity and quality of wetlands and their distribution is essential to wetland managers. In the past, the information on wetlands was usually collected by field investigation. The physical characteristics of wetlands make fieldwork expensive, time-consuming and often inexact (Harvey and Hill, 2001). The development of spatial technologies, including remote sensing, opens a door for the acquisition of wetland information. More and more wetland researchers use remotely sensed data in their

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researches (Ozesmi and Bauer, 2002).

In the past two decades, knowledge rule-based methods have been applied extensively to land use/cover classification and have proven to be effective (Moore *et al*., 1991; Friedl *et al*., 1999; DeFries and Chan, 2000; Pal and Mather, 2003; Carvalho *et al*., 2004; Mitra *et al*., 2004; Na *et al*., 2009). However, little effort has been made on research on freshwater wetlands using object-oriented relationship features in space as an aid for the classification of wetlands (Huang and Jensen, 1997; Liu *et al*., 2006). In this paper, the relationship between neighboring objects has been used as variables for the classification of wetlands.

Wetlands can be described as transitional zones with a mix of characteristics of terrestrial areas and the characteristics of aquatic environments and they are the edges of rivers and lakes and in the inter-phase between uplands and adjacent water bodies. They exhibit a mix of characteristics of uplands and water bodies. Since Hongze Lake is a transitional lake, the water levels change frequently. This variable hydrological regime brought about variable soil and vegetation. The combination of hydric soils, hydrophytic plants and wetland hydrology exhibits colorful wetland characteristics which lead to the colorful display of wetlands on remotely sensed imagery. The complexity of wetland conditions makes it difficult for traditional pattern recognition methodology to identify them. The combination of object-oriented method and the knowledge-based rule method can explore further the potential of relationship features in identification of wetlands from uplands. In this paper, several relationship features have been used for the identification of different kinds of wetland vegetation in the study area.

2 Methodology

2.1 Study area

Hongze Lake is the fourth biggest freshwater lake in China, located between 33º06'–33º40′N, 118º10'–119º00′E (Fig. 1). It covers approximately 1597 km^2 at an average lake elevation of 12.5 m (Wang and Chen, 1999). Of the major rivers that drain into the lake, the Huaihe River contributes about 87.3% of the fresh water (Wang and Dou, 1998). The lake mainly drains through the Sanhe River and Gaoyou Lake into the Changjiang (Yangtze) River, accounting for 60%–70% of the outflow (Chu, 2001). Other outlets for draining the lake are the northern Jiangsu Main Irrigation Canal and the New Huaishu River (Gao *et al*., 2010). The maximum depth of the lake is 4.37 m with an average depth of 1.71 m. There are a variety of wetland plants in Hongze Lake and nearby riparian zones, especially in the area surrounding the mouth of the Lihe River which meets the lake. From the bank of the lake to deeper parts of the lake, *Phragmites communis*, *Nelumbo nucifera*, *Zizania Caduciflora*, *Euryale ferox*, *Trapa bispinosa*, *Potamogeton malaianus*, and *Myriophyllum spicatum* are the dominant plant types (Dai and Yang, 2002; Hu and Yang, 2004). The wetlands are of great importance for wintering waterfowl, particularly *Otis tarda*, *Ciconia nigra*, *Ciconia ciniconia* and *Grus japonensis*. Two species of cranes (*Grus Japonensis* and *Grus grus*) winter here in large numbers (Lu, 1995; Hu and Yang, 2004; Gao *et al*., 2010).

In the last three decades, due to severe anthropogenic disturbances, approximately 209 km^2 of wetlands have been lost, accounting for nearly 13% of the total area of the lake (Ruan *et al*., 2005). A lot of natural wetlands have been reclaimed for crab aquaculture (Gao *et al*., 2010). Many tributaries of the Huaihe River are parallel. This often leads to drainage into the Huaihe River at nearly the same time as precipitation occurs in the watershed, which causes flooding. Since Hongze Lake is a transitional lake and the Huaihe River drains its water into Hongze Lake, the water levels of the lake often undergo large changes, both annually and seasonally (Wang and Chen, 1999). The annual and seasonal changes of water levels in the lake significantly influence the quality and quantity of wetlands (Gao *et al*., 2010).

The study area includes most parts of the National Jiangsu Sihong Hongze Lake Wetland Nature Reserve. The reserve lies between 33º10′40″–33º20′27″N and 118º13′09″ –118º28′42″E (Wang *et al*., 2006). The total area of the reserve is 23 453 ha, in which the core area is 2205 ha, the buffer area 4659 ha, and the test area 16 589 ha, accounting for 9.4%, 19.9% and 70.7% of the total area of the reserve, respectively (Yang, 2003). The reserve is set up for the protection of Hongze Lake wetland ecosystem and rare birds. The study area is characterized by a great diversity of landscape, and there is a variety of wetlands in this area (Table 1).

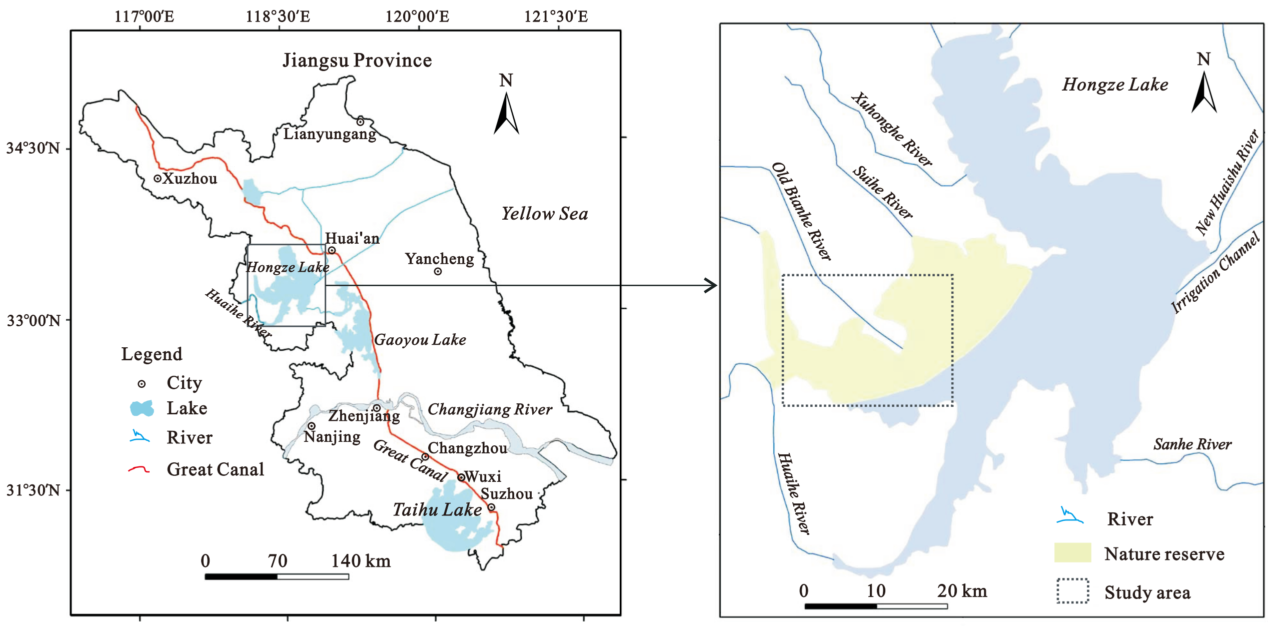

Fig. 1 Location of study area

Table 1 Land use/cover classification for study area

Code	Class	Description
1	Submerged	*Potamogeton malaianus*, *Myriophyllum spicatum*, *etc*.
2	Emergent	*Phragmites autralis*, *Zizania caduciflora* and floating-leaved plants such as *Euryale ferox*, *Trapa natans*
3	Open water	Lake water body, natural river, canal, channel, reservoir and ponds, without any wetland plants
4	Aquaculture	Fish ponds
5	Farmland	Rice paddy and dryland
6	Forest	Include natural and planted forest
7	Impervious	Land for settlement, communication, other industry and consolidated bare soil

2.2 Data preprocessing

In this study, a Landsat ETM+ imagery acquired on September 22, 2002 was used as the main data source. Autumn is selected for the time of mapping because the variation of water levels and water quality in Hongze Lake in autumn is smaller than that in other seasons. Moreover, the water level of the lake in autumn is more stable than that in summer and spring. In winter, most kinds of wetland vegetation are dead. Therefore, autumn is the best time in one year for the mapping of wetland vegetation in Hongze Lake. The imagery was geometrically corrected by using ground control points from the topography at the scale of 1 : 50 000 with less than 1 pixel root mean square (RMS) error. The Universal Transverse Mercator (UTM) map projection was adopted with the World Geodetic System 1984 (WGS84) datum, zone 50. Nearest re-sampling method was used. Then the imagery was cropped to cover the core part of Jiangsu Sihong Hongze Lake Natural Wetland Reserve and its buffer area. The reserve is the only area where wetland vegetation has been less influenced by reclamation. Since the study area is relatively flat, the image was not orthorectified.

2.3 Field investigation and reference data collection

Reference data to verify satellite image interpretation include field measurements coupled with ancillary data, such as maps, aerial photos and interviews with local people. Field investigations were conducted in spring and late autumn and as possible as in the seasons close to the satellite overpasses, i.e. during March 26 to 31, 2002, September 16 to 25, 2004, and October 25 to November 1, 2004. At first, 450 samples were generated randomly using pre-classified imagery and maps. Then the samples were overlaid over imagery and maps for checking to make sure that they were not near or at the edges of different types of objects. If they were near or at the boundaries, other replacement points were sought within a radius of 500 m. Then the samples were uploaded into handheld GPS receiver for guidance of the field investigation. Representative areas of each type of wetlands were visited in the field. For each type, dominant species, percent coverage, and the intermediate environment were recorded.

2.4 Image segmented as classification context

Bands 1 to 5 and 7 of Landsat 7 ETM+ imagery were used for segmentation and classification by using Definiens Professional 5. The main purpose of segmentation was to overcome the 'salt and pepper' effect existing in per-pixel classifications (Stuckens *et al*., 2000; Voorde *et al*., 2007). The segmentation routine in Definiens is based on a multiresolution segmentation strategy that utilizes a type of region growing approach (Stow *et al*., 2008). Segmentation is controlled by scale and shape. After trial and error, the parameter scale was set to 10 to achieve realistic segmentation of wetland vegetation types. Other parameters were set as follows: Color : shape = 7 : 3, Compactness : Smoothness = 3 : 7. Based on experiments, segmentation was run at only one level.

A total of 126 Representative areas of wetlands and other types of objects were selected for training based on the field investigation and visual interpretation of the imagery. In this paper, the Standard Nearest Neighbor Classifier in Definiens, which is based on a feature space distance to training samples, was used for the classification of the segments (Yu *et al*., 2006; Stow *et al*., 2008).

The accuracy of the object-oriented classification results were examined using an object-based accuracy assessment approach. Object-based accuracy was assessed by first selecting test objects, defined as image-derived segments that correspond to field-observed types and visually interpreted objects of wetland vegetation and other land cover. None of these segments were used for training purpose (Stow *et al*., 2008).

The object-oriented classification results were used as a context for further rule-based classification. The patch-based GIS features such as neighboring relations were computed as variables for further rule-based classification (Fig. 2).

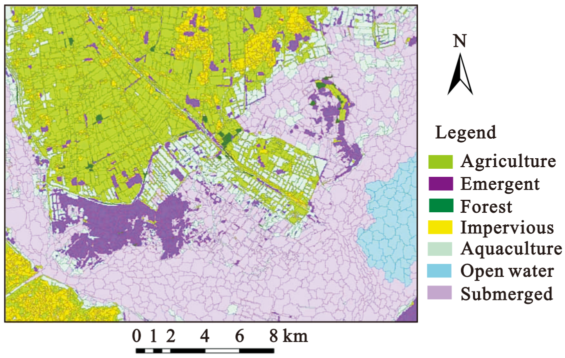

Fig. 2 Object-oriented classification results

2.5 Feature selection and derivation

When identifying wetlands, relations to neighbor objects may be useful feautures because of the spatial relationship of objects in distribution. These relations can be represented by using measures such as 'Distance to', 'Border to', 'Relative border to', *etc*. (Benz *et al*., 2004). In this paper, the relationships were rasterized into layers to aid the identification of wetlands and improve the accuracy of classification (Fig. 3).

In general, texture consists of visual patterns or spatial pattern of pixels that may have statistical properties, structural properties, or both (Haralick *et al*., 1973; Laba *et al*., 2010). Texture of imagery has been widely applied to the classification of wetlands and proven to be effective (Wright and Gallant, 2007; Laba *et al*., 2010). There are many ways to descripe texture. The Gray-level Co-occurrence matrix put forward by Haralick has been proven effective for the identification of wetlands (Armenakis *et al*., 2003; Töyrä and Pietroniro, 2005). In their paper, eight statistical metrics were adopted, including mean, variance, homogeneity, constrast, dissimilarity, entropy, angular second moment,

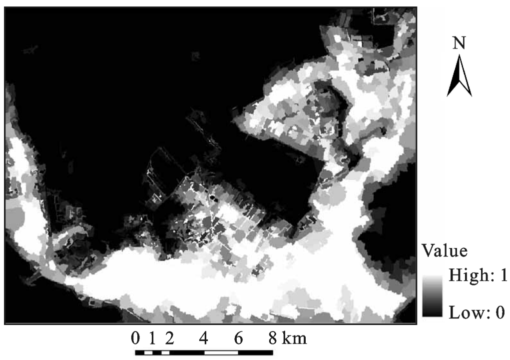

Fig. 3 Object-relation feature: Relative border to submergent features

correlation (Haralick *et al*., 1973; Haralick, 1979). The size of moving windows, step and direction are three important parameters of a Gray-level Co-occurrence matrix. After several experiments, it was found that setting the size of the moving window, step and direction to 5 × 5, 1, and 45º achieved the best separability of wetlands and upland objects.

Since artifical wetlands such as rice paddy and fish ponds have more regular boundaries than natural wetlands, shape index may be an effective feature to separate natural wetlands from artifical wetlands such as rice paddy and fish ponds. The formula of the shape index is as follows:

$$S = \frac{0.25P}{\sqrt{A}} \tag{1}$$

where S is shape index of each patch, P and A are the perimeter and area of each patch, which are generated in image segmentation.

Water depth is one of the important physical factors influencing the wetland vegetation development and its density (Davranche *et al*., 2010). The distribution of aquatic vegetation and their variability in space are to some degree controlled by the water depth (Narumalani *et al*., 1997). According to field investigations, erect macrophytes usually grow at the water level of 12 m to 13 m, floating-leaved macrophytes at the water level of 11.5 m to 12.0 m and submerged aquatic vegetation at 11.0 m to 11.5 m. In this study, a Digital Elevation Model (DEM) was derived from field measurements and from topography of 0.5-m accuracy (Fig. 4). The DEM was generated in ArcGIS at the same spatial resolution as that of the ETM+ image. Then the DEM was superimposed over the image and the non-overlayed part was excluded.

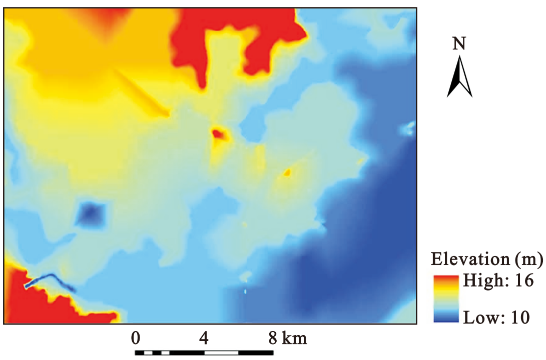

Fig. 4 Digital Elevation Model of study area

2.6 Rule generation and pruning

Rules for the division of decision space can be generated using experts′ expertise and experience or generated automatically from computer algorithms. Graphically a set of decision rules are like an up-down tree, called a decision tree. In the process of recognition, a dataset is partitioned into smaller subdivisions on the basis of tests defined at each branch. A dataset is classified squentially untill the preset conditions are met. Then a class label is assigned to each observation of a leaf node into which the observation falls (Friedl and Brodley, 1997). Classification and Regression Tree (CART) is an increasingly popular decision tree algorithm available through widely used statistical packages, such as S-Plus (Venables and Ripley, 1997; Lanrence and Ripple, 2000). It operates by recursively splitting the dataset based on statistical test that increases the homogeneity of observations in the resulting descendant nodes (Breiman *et al*., 1984; Friedl and Brodley, 1997). The result of the CART algorithm is a classification tree. Each path through the tree will be a series of dichotomous splits and the tree is composed of a series of knowledge rules (Lawrence and Wright, 2001). In this paper, CART was adopted for the generation of rules using 450 reference samples as training data. Each sample has a series of attributes such as x, y coordinates, six channels of ETM+, eight texture metrics, elevation, relationship of neighbors, *etc*. The training samples were introduced into CART4.0 algorithm and rules were obtained.

2.7 Classification of imagery

The decision tree was pruned and imported into the Environment for Visualizing Images (ENVI) decision tree classifier for the classification of the study area using the combination of different sources of data. Finally, the classification results from the decision tree was integrated and further improved by using the object-oriented classification results. The patches of object-based classification were used as units for the final classification. First, the class label for the majority of pixels within a patch defined by the decision tree is determined. Then if the class label of the patch determined by decision tree matches that determined by the object-based classifier, the class label will be the final class label of the patch. If the class label of the patch determined by decision tree does not match the one determined by object-based classifier, the final class label of the patch will be the one determined by the decision tree because the decision tree has used more variables in its determination than object-based classifier, especially the elevation data, which is a good variable for the identification of the wetlands from upland vegetation.

2.8 Evaluation of classification accuracy

The accuracy of classification results were estimated by samples obtained from a randomly stratified sampling method with a minimum of 30 samples per class (Congalton, 1991). This was done by creating a mask that covered areas with reference data. The mask was superimposed over one of classification maps and samples were extracted randomly from each class within the mask. Sampled data were compared against reference data to define the correct class attribute. While overlaid over reference data, the points at the edge of objects are removed for the class uncertainty determination. In total, 450 samples were derived, but after removing the points measured at the edges of objects, 416 points remained for the evaluation of the classification accuracy. A confusion matrix was used to evaluate classification accuracy (Table 2 and Table 3).

3 Results and Analyses

Object-based classification shows that there is some confusion between upland objects and wetlands. For example, rice paddies are misclassified as emergent wetland vegetation. Classification results of the decision tree, to some degree, eliminated the misclassification between wetland and upland objects due to the use of spatial relationship such as the elevation, the relative location of objects in space, *etc*. In most cases, an upland object is adjacent to other upland objects and aquatic objects neighbor aquatic objects. In the study area, it is noticeable that submerged aquatic vegetation is usually adjacent to open water or emergent vegetation. Agricutural landscape types such as rice paddy and dryland are usually adjacent to impervious types such as built-up areas.

Table 2 Accuracy assessment of classification without object-oriented constraint

Class name	Class code	1	2	3	4	5	6	7	Row total	User's accuracy (%)
Submerged	1	87	2	1	1	0	0	0	92	94.57
Emergent	2	6	34	0	7	2	0	0	51	66.67
Open Water	3	5	2	51	2	0	0	0	63	80.95
Aquaculture	4	1	0	0	45	3	2	1	56	80.36
Farmland	5	1	0	0	2	60	7	9	84	71.43
Forest	6	0	0	0	8	13	21	2	50	42.00
Impervious	7	0	0	0	0	0	0	41	48	85.42
Column total		100	38	52	65	78	30	53	416	
Producer's accuracy (%)		87.0	89.4	98.0	69.2	76.9	70.0	77.3		

Notes: Overall accuracy = 81.49%; Overall kappa statistics = 0.7676

Table 3 Accuracy assessment of classification with object-oriented constraint

Class name	Class code	1	2	3	4	5	6	7	Row total	User's accuracy (%)
Submerged	1	87	2	1	3	0	0	0	94	92.55
Emergent	2	6	35	0	5	1	0	0	49	71.43
Open water	3	5	1	51	1	0	0	0	61	83.61
Aquaculture	4	1	0	0	51	4	2	1	63	80.95
Farmland	5	1	0	0	4	66	7	9	92	71.74
Forest	6	0	0	0	1	6	21	0	34	61.76
Impervious	7	0	0	0	0	1	0	43	51	84.31
Column total		100	38	52	65	78	30	53	416	
Producer's accuracy (%)		87.00	92.11	98.08	78.46	84.62	70.00	81.13		

Notes: Overall accuracy = 85.10%; Overall kappa statistics = 0.8204

However, the 'salt and pepper' effect is still a serious problem in the classificaion results of per-pixel decision trees. For example, edges of fish ponds with grasses were classified as emergent wetland vegetation, while edges without grasses were classified as impervious land cover types (Fig. 5). While in the object-based classification, the edges were classified as aquaculture objects because of use of texture when classifying the fish ponds. However, there were also some problems with the classification results by the object-based classifier. For example, at the edge of the lake, some segments extend into the lake because of the similarity of textural features of the upland objects and the wetland objects. Per-pixel classification of decision trees has to some degree overcome the problem due to the use of more variables in determining the class label. The constrained classification results have eliminated the 'salt and pepper' effect (Fig. 6). In total, 416 points were used for the accuracy assessment of classification without object-oriented constraint and the one with object-oriented constraint (Table 2 and Table 3).

Submerged aquatic vegetation occupied a large part of the study area, accounting for 28.87% of the study area (Fig. 6). Due to the action of flow from the Huaihe River, the suspended matter carried by the Lihe River and other rivers are deposited in the area (Fig. 1). Most of time, the water level here is from 0.7 to 2.0 m, and the lake bottom can be seen from the water surface. Since it has been protected by the establishment of the Jiangsu Sihong Hongze Lake Wetland National Reserve, the big patch of emergent vegetation exists in the study area. *Phragmites communis* is the dominant species of emergent vegetation, which accounts for 9.63% of the study area.

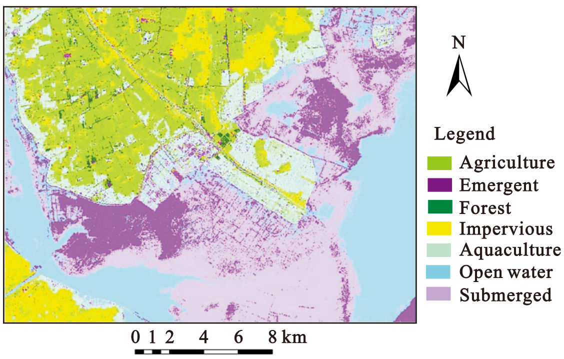

Fig. 5 Classification without object-oriented constraint

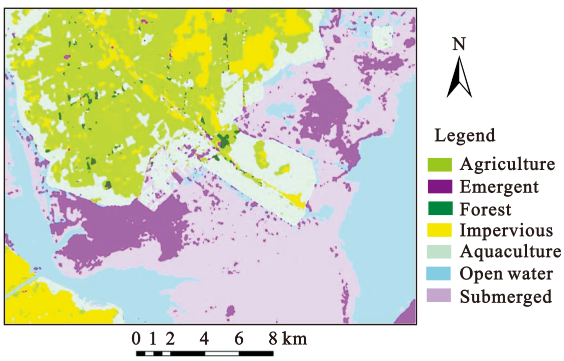

Fig. 6 Classification with object-oriented constrai

As shown in Table 2 and Table 3, submerged aquatic vegetation is misclassified as emergent vegetation, open water, and aquaculture. Submerged aquatic vegetation is misclassified as emergent vegetation because sparse emergent vegetation and open water have similar representation in imagery to submerged aquatic vegetation. Due to the sparse density of submerged aquatic vegetation or the influence of deeper water, some has been misclassified as open water. As for submerged aquatic vegetation, the classification accuracy of both methods is nearly similar. The producer's accuracies for open water are the same for both methods at 98.08%, indicating that open water is more easily identified than other objects in the study area. The producer's accuracy for emergent wetland vegetation with the decision tree classifier (method 1) is a bit lower than the corresponding number with decision tree constrained with object-based classification results (method 2). The producer's accuracy for aquaculture with method 2 was improved by 9% more than that with method 1, indicating that method 2, with constraint of segments has not only overcome the 'salt and pepper' effect, but also solved the problems relative to the classification of complex objects. Fish ponds are complex objects, consisting of standing water and pond edges. In the study area, grasses or trees usually grow over the edge of fish ponds. The per-pixel classifier can classify the standing water of fish ponds as open water and the edges of fish ponds as farmland or forest objects while the object-based classifier can overcome the problems by processing the standing water of a fish pond and its edges as a whole object. That is why method 2 with constraint from results of object-based segmentation can improve the producer's accuracy for aquaculture.

The producer's accuracies for farmland and impervious objects with method 2 were also higher than method

1, proving that object-based classification constraint can to some degree solve the problems of transition zones between two kinds of objects. As for the farmland, there is variation even within one field. Per-pixel classifiers can not solve this problem. For the impervious objects, there is a lot of disturbed land between houses. The land is usually used for growing vegetables or just left as weed land although they are actually transitions between houses. Object-based classifier can process them as a whole unit while per-pixel can not. The producer′s accuracy for method 2 is similar to that for method 1. The user′s accuracies for submerged aquatic vegetation are nearly the same with both methods. Some emergent vegetation, aquaculture and open water were misclassified as submerged aquatic vegetation due to the sparse density of emergent vegetation, being too wet for rice paddies. The existence of grass on the water surface in some fish ponds function as food for fish or crabs. Pond weed (*Potamogeton crispus*) and goldfish weed (*Ceratophyllum demersum*) are common aquatic vegetation placed in fish ponds as fish and crab food. The producer′s accuracies and the user′s accuracies for forest with both methods are less than the ones for other types of objects. The user′s accuracy for emergent vegetation with method 1 is lower than the corresponding value for method 2, but both are not high. Due to the mixed pixels consisting of open water and emergent vegetation or submerged aquatic vegetation, misclassification of such mixed pixels as emergent vegetation or other classes degrades the user′s accuracies or producer′s accuracies for emergent vegetation. In some parts of the study area, due to the high density of submerged aquatic vegetation and exposure at the water surface, submerged aquatic vegetation appears similar to emergent vegetation in spectral characteristics sometimes. This caused the misclassification of submerged aquatic vegetation as emergent vegetation. In some fish ponds, plants such as water hyacinth are used as food for fish or crabs. This caused the misclassification of aquaculture as emergent vegetation. The narrow strips of fish pond edges caused the existence of mixed pixels and the misclassification of parts of aquaculture as emergent vegetation.

Linear features or narrow strips such as small rivers or channels have been misclassified as other classes. These linear features or narrow strips usually consist of only one pixel in width. This caused them to be classified as other classes by method 2 when constrained by segments from object-based classification than by method 1. The user′s accuracy for open water with method 2 is the same as method 1. The user′s accuracy for aquaculture with method 2 is the same as method 1. The overall accuracy of method 2 is nearly 4% higher than the corresponding class type with method 1.

4 Conclusions

Decision tree classifiers can fully explore the variables and find the optimal variables for the identification of wetlands in this study. Not only the traditional variables such as spectral, textural and elevation features can be included in the dataset for decision tree classifiers, but also the variables such as spatial relations can be included in the dataset. In this paper, the variables such as elevation, relationships such as ′Distance to′, ′Border to′, ′Relative border to′ have been used for identification of wetlands. This, to some degree, has improved the identification of wetlands. It is shown that the use of object-oriented classification results as a constraint has improved the overall accuracy from 81.49% to 85.10%, the kappa coefficient from 0.7676 to 0.8204.

The submerged aquatic vegetation accounts for 28.87% of the study area, emergent aquatic vegetation 9.63% of the study area. Due to the protection of the Jiangsu Sihong Hongze Lake Wetland Natural Reserve, there are two relatively complete patches of erect emergent in the area. *Phragmites communis* is the dominant species of the emergent wetland landscape in the study area.

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