

WETLAND MAPPING USING SUBPIXEL ANALYSIS AND DECISION TREE CLASSIFICATION IN THE YELLOW RIVER DELTA AREA

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ABSTRACT:

A lot of wetlands exist in the Yellow River Delta area, Shandong China and exhibit significance for the delta ecological environmental evolution and animal habitat protection. It is important for wetland protection and management to accurately map the wetland distribution by remote sensing due to the fact that the estuary area changes very fast. This study tries to combine subpixel analysis of remotely sensed data with decision tree classification to improve the wetland mapping in the delta area. A two-step classification technique was proposed trying to make use of a priori knowledge of wetland compositions. First, a subpixel analysis technique was applied to remotely-derived reflectance data using in-site spectra to extract abundance images for each component material of the wetlands. A suitable set of endmembers were selected for the unmixing analysis. A classification scheme of wetlands was then created and used to classify the abundance images into various wetlands and non-wetlands. The approach combines quantitative analysis (subpixel unmixing) with qualitative decision (classification), and incorporates with human knowledge during the whole process of analysis. An ASTER image of surface reflectance was acquired for the study area and used to evaluate the proposed approach. The approach was implemented in RSI ENVI/IDL environment. Twelve wetland and non-wetland covers were identified using the technique and the result was then assessed with field verification and the land use data that was acquired by other method. The overall accuracy of the wetland mapping is about 88.7% and the Kappa coefficient is 0.86.

1. INTRODUCTION

Wetland ecosystems are the most naturally significant and biodiverse ecological landscapes and important human living environments (Lu, 1990). Real-time access to spatial and temporal distribution of wetlands, accurately understanding the status of wetland resource, and monitoring dynamic changes of the wetlands are truly necessary for wetland study and management. It has been proven that remote sensing technology is extremely useful and has been widely used in the extraction of wetland information, investigation of wetland resources, and monitoring of wetland changes (Edward et al., 1997). However, conventional pixel-based classification of remotely sensed data can not fully meet the requirements of wetland mapping due to the complexity of wetlands ecosystem itself although textural features, wetland soil characteristics, vegetation and different habitats imaging characteristics of wetlands were studied and incorporated into wetland mapping (Franklin et al. 1994; Zhang 2000; Li and Guan, 2002). These methods improved conventional spectrally based classification and achieved better wetland mapping more or less. However, they still have some limitations and can't address the mixture problem in mid- or low-resolution remote sensing data (Wang, 2006). Furthermore, it is difficulty to well categorize wetland classes using conventional spectral classification of remote sensing imagery due to the diverse spectra of different wetland compositions of a wetland type.

In this paper we proposed an approach for wetland mapping that combines subpixel analysis with decision tree classification based on the mechanism of remote sensing based information

extraction for wetlands. The approach was implemented using RSI ENVI4.0 and IDL environment, and an ASTER image that covers the Yellow River Delta wetland area was used to test the proposed technique. Twelve classes of wetland covers and non-wetland covers were identified using the proposed technique: coastal shoals, drains, salt field, estuary water, aquaculture ponds, paddy fields, shrub wetlands, salt swamp, residential, bared land, farming land, and undivided land cover. The classification result was then assessed with field verification and the land use data that was acquired by other method.

2. METHODOLOGY

Most classification algorithms are based on spectral information of each pixel of an image and don't take into account the problem of mixed pixels (Roberts et al., 1998; Wang, 2006). If a pixel of remote sensing images contains several land cover types, such pixels are known as mixed-pixels (Zhu, 1995). The spectrum of a mixed pixel is a mixture of all the surface materials in the pixel (Liu and Liu, 2001). The studies of the mixed-pixel problem can be found in early literature. Atkinson (2000) applied subpixel analysis in the extraction of snow and precipitation from radar images by decomposing the abundances and membership uncertainties of pure land covers in a mixed pixel based on the training samples (Li and Zheng, 2000).

The composition of wetlands is basically sand/soil, vegetation, and water body. Each wetland class is a combination of these basic materials with different proportions. The spectra of mixed

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pixels in the image are mixture of spectrum of water, soil and vegetation. Thus, subpixel analysis is useful for decomposing wetland pure materials and the abundance of each material can be extracted from the image. After that, a decision tree based classifier will be used to categorize wetland classes. Thus, a two-step classification technique is proposed for the wetland mapping which tries to make use of a priori knowledge of the wetland compositions. The basic steps of the approach can be depicted as follows and illustrated in Figure 1.

2.1 Extraction of Wetland Components

A group of wetland component materials termed as endmembers are identified by field investigation and initial analysis of the imagery in question. An automatic endmember extraction method was used to extract the spectrally pure materials of wetland, and the knowledge of the wetland compositions in the study area was also used in the process of endmember selection.

Generally reference spectra of endmembers of interest can be extracted from the spectral library and field measurements, otherwise the image in question is used to extract image endmembers directly due to lack of field measurements (Lv et al., 2003). Basically three wetland endmembers were identified from the image: vegetation, soil/sand and water body which can form the different wetland classes in the study area.

2.2 Unmixing of Subpixel Abundance

To establish a mixture model of different endmember spectra, the reflectance of an image pixel is usually represented as a function of endmember spectra and their area proportions, or as a function of endmember spectra and other surface parameters (Charles and Karnieli, 1996). The mixture models include linear mixture model, geometric optical model, stochastic geometric, probability model and fuzzy model (Borak and Strahler, 1996). Considering the nature of wetland endmember mixture, a linear subpixel analysis model was applied to remotely-derived surface reflectance data using endmember spectra that is extracted from the image by PPI approach to extract abundance images for each component material of the wetlands.

2.3 Decision Tree Classification

The decision tree classifier is applicable to noisy data and able to select the most suitable features for a classification task. The classification process is relatively easy to understand and interpret for the user (Friedl and Brodley, 1997). When the surface land covers are complex the decision tree classifier may performs better than other statistically based classifiers (Running et al., 1995; Li and Zhang, 2003). After the extraction of endmember abundances, a classification scheme of wetland was created and a decision tree classification was used to classify the abundance images into different wetland and non-wetland land covers. In the course of the classification, a wetland class should be meaningful and is not just a composition of the basic wetland materials. Some knowledge of the wetlands in the study area should be incorporated into the forming of the classification scheme.

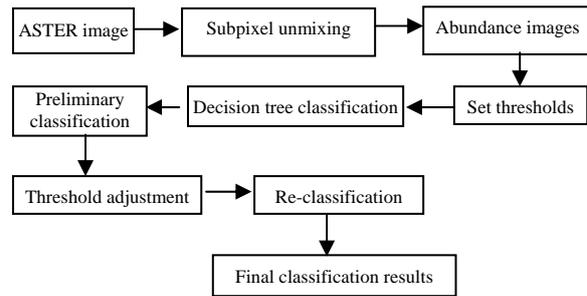


Figure 1. Flowchart of the wetland classification

3. AN EXAMPLE

3.1 Extraction of Wetland Components

A portion of an ASTER that covers part of the Yellow River Delta area was processed and used to test the performance of the proposed approach. The analysis was implemented using RSI ENVI package and IDL programming environment. The ASTER surface reflectance data was transformed using MNF analysis, and the first six MNF bands were selected for further analysis. The PPI method implemented in the ENVI system was then used to extract wetland endmembers. The threshold value for the selection of pure pixels is 150. The wetland endmembers (water, soil/sand and vegetation) (pure pixels) were visualized in Figure 2 and 3. After that, the three endmembers and linear subpixel mixture model were used to unmix the ASTER image and three abundance images were generated (Figure 4).

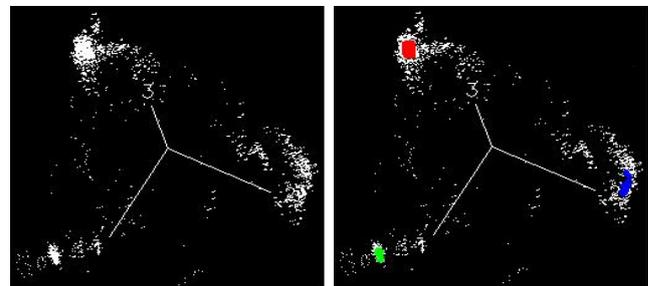


Figure 2. Selection of pure pixels with the n-Visualizer tool

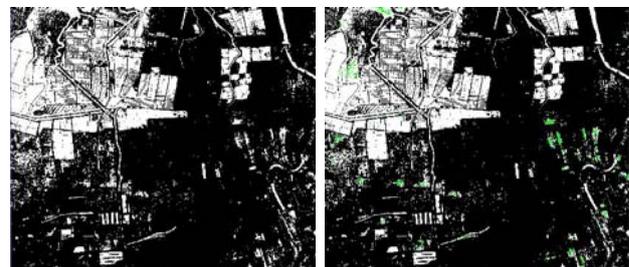


Figure 3. Visualization of the pure pixels in the image

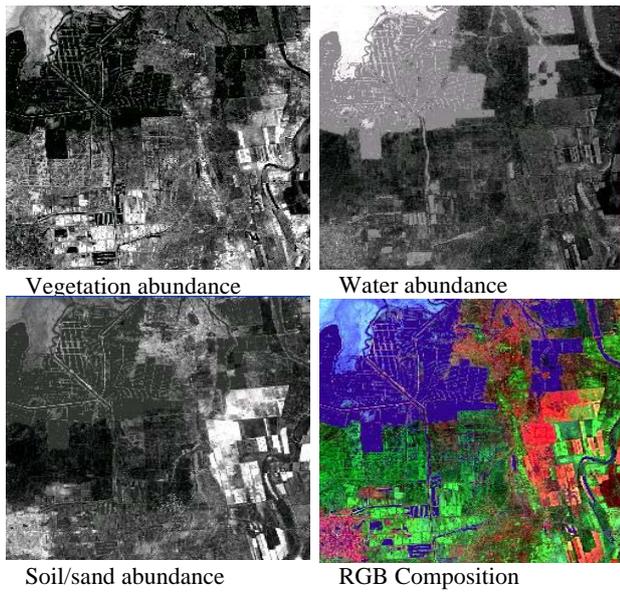


Figure 4. Abundance images of the wetland compositions

3.2 Classification

Actually wetland classes are combinations of these three “pure” materials with various proportions of them. Thus, a decision tree base classifier was formed and used to classify the three abundance images in the study area. The classification flowchart was illustrated in Figure 5.

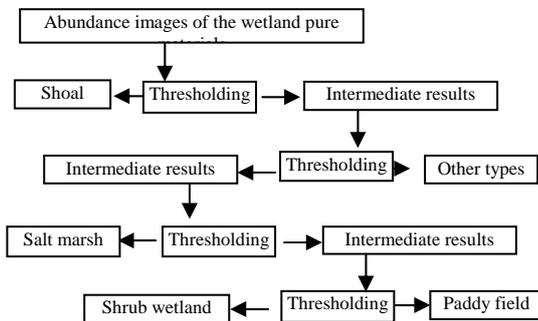


Figure 5. The diagram of the classification

The coastal shoal land is easy to be discriminated due to more water component than other wetland types. Based on the relative soil/sand and water contents, bare soil land and residential land can be identified. Shrub wetland, salt marsh and paddy field can be discriminated according to their vegetation and soil/sand abundances. A part of rules for the classification are listed as follows:

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If water > 0.85, then class = shoals
Elseif Soil > 0.3 then class=other land use
Elseif vegetation > 0.1 and Soil > 0.1 then class = paddy field
Elseif class= shrub wetland;
Else class = salt marsh
Endif
    
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The determination of the threshold values is interactively adjusted and optimized based on the classification results. Once the classification rules are determined then the classification was performed to the ASTER image. The result was shown in

Figure 6. Totally twelve classes were discriminated from the abundance images using the proposed approach.

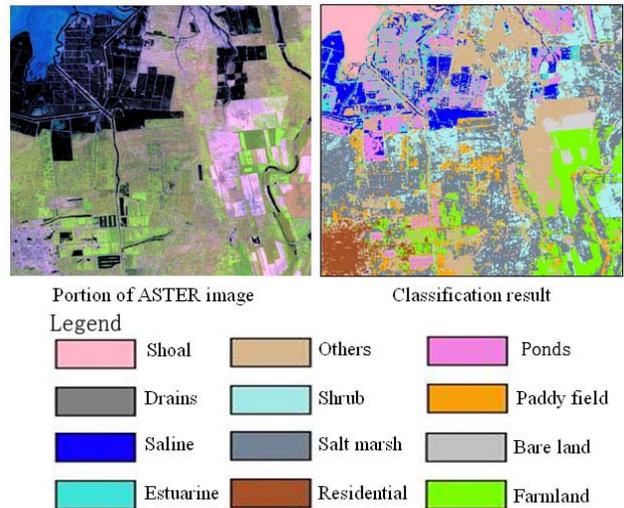


Figure 6. Classification Result

3.3 Assessment of Classification Accuracy

The classification result was assessed using field verification and a land use map in the study area that was derived from other data source. The overall accuracy of the classification is 88.7% and the Kappa coefficient is 0.86. The assessment indicates that the proposed wetland classification approach can achieve good classification in the study area. Some wetland classes such as shoals, salt fields, river estuarine and ponds have similar spectral characteristics and are usually difficult to be discriminated using pixel-based classification methods. However, they can be well identified from the abundance images using the proposed approach.

3.4 Comparison

For purposes of further test of the method we proposed in the study, the maximum likelihood classification (MLC) was used as a comparison. Two more data sets: ETM+ and SPOT-5 were also used in the comparative study. The MLC method was applied to the three data sets while the proposed approach was just used to classify the ASTER image. The results (Table 1) indicate that the ASTER data can achieve better result due to more SWIR and TIR bands than ETM+ and SPOT-5 data sets. On the other hand, the proposed approach can outperform the MLC classification in the case of the ASTER data being applied.

Methods	Data	Overall accuracy	Kappa
MLC	ETM+	83.5	0.76
	SPOT-5	82.4	0.76
	ASTER	85.9	0.74
The proposed approach	ASTER	88.7	0.86

Table 1 Comparison between the MLC and proposed approach

4. CONCLUSION

Wetland mapping is significant for wetland environmental monitoring and management. Wetland "pure" compositional materials are basically vegetation, water and bare soil/sand, and a wetland class is somewhat a linear mixture of these materials. This study proposed an approach that combines subpixel analysis with decision tree classification to form a wetland classification scheme. The approach can incorporate human knowledge into the process of analysis.

The experimental study in the Yellow River Delta area shows that the proposed approach can reduce difficulty in classifying spectrally similar wetland classes, and consequently improves the classification accuracy. The comparative study between the maximum likelihood classification and the proposed approach also indicates that better result of the wetland classification can be achieved by our method. Further study may be focused on the extraction of more spectrally pure wetland components (e.g. sub-vegetation types) and field-measured spectral library for wetlands should be built in future work.

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