Identification of Inland Fresh Water Wetland Using SAR and ETM+ Data

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Abstract—**The main aim of this paper was to explore the potential of SAR data, in combination with optical remote sensing data, in identifying inland fresh water wetland from crop, especially rice paddy. The test area is a part of Hongze Lake, the fourth biggest fresh water lake in China. It is one of important wetlands for migratory birds in China. Due to unreasonable exploitation of wetland resources, the lake is facing a great loss of wetland. In Hongze lake watershed, Jiangsu Provincial Sihong Hongze Lake wetland ecological reserve was established for the preserve of wetland ecosystem and rare species in the watershed. In the processing of the dataset, clustering algorithm ISODATA was employed firstly to generate initial classification results for sample selection. Then, 1500 samples were taken in total by using stratified random sampling. These samples were superimposed on the screen on top of rectified aerial images. The land cover class at each point was determined based on field investigation and visual interpretation. 900 samples of them were for training and the other for the assessment of classification accuracy. Attributes of samples such as the digital number values of six bands of ETM+(TM1-5, 7), texture, DEM and 4 components of principal components analysis of six bands of ETM + data, were fed into the CART (Classification and Regression Tree) algorithm for the generation of knowledge rules. Because the training observations were evenly distributed among classes, the class assignment at each terminal node was determined by the majority of per-class observations at that node. Then, decision tree classifier was applied to the imagery of ETM+ for the classification of landuse/cover in the whole study area. RADARSAT SAR C-band was classified into four classes: lowest backscatter, low backscatter, medium and high backscatter. The results from two data sources were combined by using rules. The results showed that the combination of the SAR data and the optical remotely sensed data have achieved the highest classification accuracy (92.3% of total classification accuracy). The results also confirmed the value of classification tree in the identification of fresh water wetland. It was illustrated that radar data was a good complementary data source for the identification of wetland.**

Keywords-identification; inland fresh water wetland; SAR; optical remotely sensed data

I. INTRODUCTION

Wetland is one of the important ecosystem in the world. Although it covers only 6% of the Earth surface, it plays an important role in the global ecosystem [1]. Wetland provides a valuable habitat for a great variety of hydrologic plants, fishes, wildlife and insets. In hydrology, wetlands improve water quality, quality, recharge ground water, control floods, and protect shorelines. Therefore, the thematic information on such as the extent of wetland, its change and the trend of the change is essential to the wetland management. However, this information is difficult to be obtained using traditional ground surveys due to logistical problems and great costs of manpower, finance and time. Satellite remote sensing has become an important and cost-effective tool for wetland investigation and researches. Optical remotely sensed data are valuable and important data sources for the identification of inland fresh water wetland and were used in many researches in the past [2-7]. Since optical sensors cannot penetrate vegetation canopies, vegetated wetlands and crops such as rice were unable to be separated by using only optical remotely sensed data [8]. Synthetic aperture radar (SAR) data can provide additional information about the hydrology and ground conditions under vegetation canopies. Studies have shown that C bands of radars are suitable for detection standing water under short vegetation such as that present in marshes [9-11]. Therefore, in this paper, the combination of SAR data with optical-based remotely sensed data was explored for the identification of inland fresh water wetland in Hongze Lake in Northern Jiangsu Province.

II. STUDY AREA

Hongze Lake is located between 33o06′ —33 o 40′N in latitude, 118 o 10′ —119 o 00′ E in longitude, and the fourth biggest fresh water lake in China (Fig. 1). Its water supply is mainly from Huai River and water discharge mostly through Sanhe River and Gaoyou Lake into the Yangtze River, the rest of water discharged into East China Sea through the Northern Jiangsu Main Irrigation Canal. The average water depth of Hongze Lake is 1.77 meters, with the deepest part being 4.37 meters [12]. There are a variety of wetland plants in Hongze Lake watershed. From the bank of the lake to deeper parts of the lake, wetland plants such as Phragmites australis, Zizania caduciflora, Nelumbo nucifera, Euvyale ferox, Trapa matans, Potamogeton malaianus, Myriophyllum spicatum and Hydrilla verticillata var. roxburghii distribute. In recent nearly 30 years, the wetland has lost a lot and about 209 km2 wetland has been lost, accounting for 13% of the total area of the lake [13]. Moreover, the extent of wetland is greatly influenced by the water level of the lake. Since the construction of the Sanhe Dam, the level of water storage has been lifted significantly, and this has caused the reduction of the extent of Phragmites australis. The study area includes the most part of Jiangsu Sihong Hongze Lake Wetland Natural Reserve. The reserve lies between the longitude 18o13′9″ E— 118o28′42″E and the latitude 33o20′27″N—33o10′40″N. The total area of the reserve is 23453hm2, in which the core area is 2205 hm2, the buffer area 4659 hm2 and the test area 16589 hm2, accounting for 9.4%、19.9% and 70.7% of the total area respectively. 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 in landscape. There is a variety of wetland and upland types in this area (table 1).

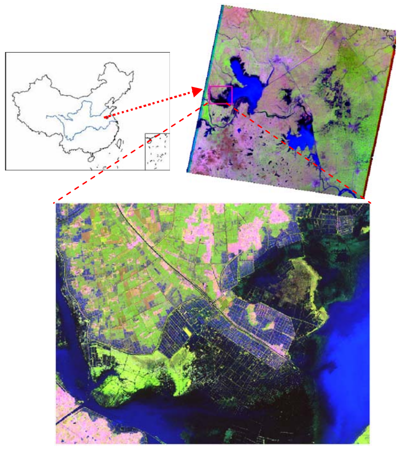

Figure 1 Location of Study area

Table1 Landuse /cover classification scheme for the study area

Class	Class name	Description
1	Emergent	Phragmites autralis, Zizania Caduciflora etc.
2	Floating-leaved	Euvyale ferox, Trapa matans
3	Submersed	Potamogeton malaianus, Myriophyllum spicatum etc.
4	Open water	Lake water body, natural river, canal, channel, reservoir and ponds, without any wetland plants
5	Fishing pond	Water areas for fishing farm such as crab and fish raising
6	Paddy	Rice paddy
7	Dryland	Dryland for vegetative and other uses
8	Forest	Include natural and planted forest
9	Built-up	Land for settlement, communication, other industry and exposed land

III. METHODOLOGY

A. Data Sources

In this paper, two scenes of RADARSAT SAR data were acquired, one was obtained (incidence angle 31.1o) on July 9, 2003, another scene of SAR acquired on July 14, 2003(incidence angle 29.8o). Optical remotely sensed data was Landsat ETM+ acquired on September 16, 2000.

Field investigation has been conducted for three times, March 26 to 31st, 2002, September 16 to 25th, 2003, October 25 to November 1, 2004.

B. Data Preprocessing

The RADARSAT SAR data were calibrated using PCI software to derive radar backscatter coefficient. The variations in local incidence angle were ignored because of flat topography in the study area. Since the radar backscatter values are in decibels, they were converted to intensity values prior to Radarsat image filtering and classification. The calibrated backscatter values were filtered by the Lee-Sigma algorithm with three iterations and square window sizes of three pixels. ETM+ was geometrically corrected and georeferenced to UTM WGS84 coordinates using ground control points first and then two scenes of SAR were registered to the geocoded ETM+. Since the study area is of floodplain, orthorectification of RADARSAT SAR and ETM+ images has not been carried out. Since the Radarsat and the ETM+ scenes have different pixel sizes, the Radarsat scenes were resampled to a pixel size of 30 m, to match the resolution of the ETM+ data.

C. Decision tree classifier

Due to spectral confusion with other land cover classes and among different types of wetlands, wetland classification was difficult. However, the combination of multi-sensors data and multi-temporal data, in addition to ancillary data, is an important way for the improvement of classification of wetland. A decision tree classifier is an efficient way for representing decision processes for classifying patterns in data [14]. It recursively divides data into increasingly homogeneous subsets based on splitting criteria. At each split, the values of each explanatory variable are examined and the particular threshold value of each variable which will reduce the deviance to a greatest degree is chosen to partition the data [15]. In this paper, at first, land cover classification was conducted by using Landsat-7 ETM+ data. In addition to original six bands of ETM+ (TM1-5,7), a series of extra bands including NDVI, NDWI, TM4/TM3, TM5/TM3, and TM5/TM4 were also derived. Transformed divergence was computed for every pair of classes for the determination of their separability and optimal bands for the classification of wetland [16]. SAR imagery was classified into four types according to backscatter of radar signal: lowest or nearly lowest backscatter, low backscatter, medium backscatter, and high backscatter. Then the results of land cover classification were improved by using SAR classes.

D. *Classification Accuracy Assessment*

600 sampling points were superimposed upon false color composite of Landsat ETM+ and those points on the boundaries of objects were deleted. In the end, 450 points were remained for the evaluation of classification accuracy. The determination of classes of points was made by using aerials and field investigation. For comparison, the evaluation for classification accuracy with and without Radarsat SAR was carried out. The Kappa coefficient has been used as it accounts for all elements in the confusion matrix rather than just the diagonal elements [17].

IV. RESULTS AND ANALYSIS

A. *Classification of Optical Imagery*

ETM+ data acquired on September 16, 2000 was classified by using knowledge classifier. The study area was classified into 9 categories(table 1). Since the foliation of the emergent vegetation in September, it was difficult to be separated from crops, especially paddy rice (Figure 2).

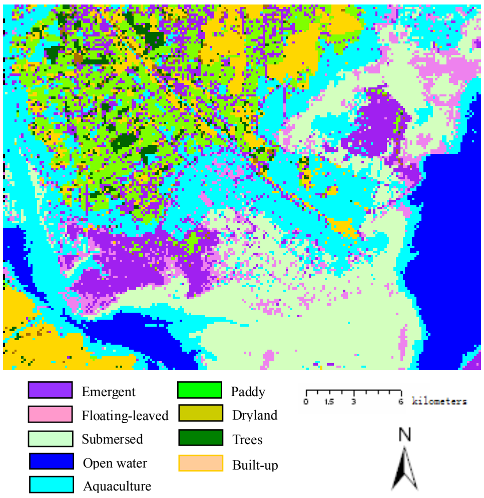

Figure 2 Results of decision tree classifier

As shown in Figure 2, aquaculture was confused with open water and emergent with paddy rice. Aquaculture was similar in spectral features with open water somewhere. Emergent vegetation (Phragmites australis dominant) was similar in spectral and textural characteristics of canopy. This leads to the confusion to the four categories.

B. *SAR-based Knowledge Classification*

SAR imagery is mad made from radar signal data. Each pixel of the image represents an estimate of the radar backscatter for an area unit corresponding to the pixel. Therefore, the brighter areas on the images mean high backscatter, while the darker areas on the images represent low backscatter. Based on the conditions of the study area, the Radarsat C band imagery can be analyzed into four types:

Open water, including some big aquaculture produce lowest or nearly lowest backscatter due to their smooth surface. Network aquaculture in the lake appears medium backscatter because of sparse emergent vegetation and submersed embankment for fear of fish fleeing and the lowering of lake lowering. High radar returns in the SAR image were from trees and buildings mainly because of corner reflection (Figure 3).

Since C-band of Radarsat SAR are capable of penetrating vegetation at some depth and detects the conditions under the canopy of the some vegetation such as paddy rice and emergent wetland vegetation, it was supposed that if the Radar SAR scene are selected carefully considering the growth stage of paddy rice and emergent vegetation, it was helpful to the separation of crops and emergent wetland vegetation. Although it was difficult to be separated between aquaculture and open water in some bands of optical remotely sensed data, it was easy for the SAR because of the smooth surface of open water.

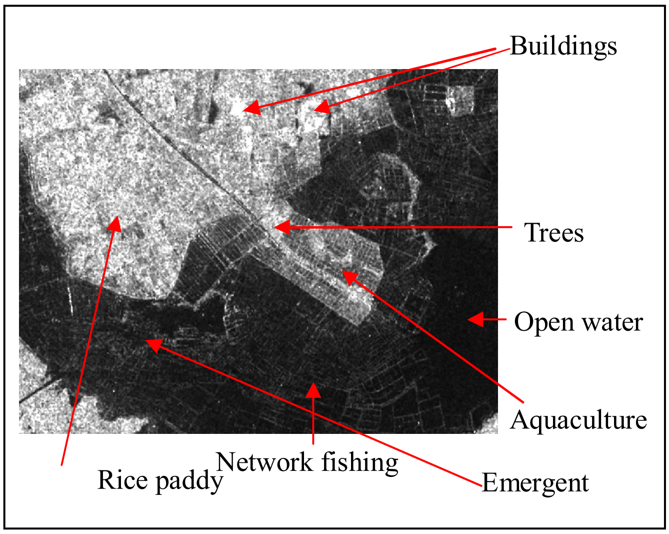

Figure 3. Land cover identified on Radarsat scene on July 9, 2003

The SAR imagery was classified into four types by using the Mahalanobis distance classification method. The results of classification with ETM+ data and those of SAR were combined by using knowledge rules:

If a pixel belongs to TM class emergent and medium backscatter, then the pixel was labeled as paddy rice.

If a pixel belongs to TM class emergent and low backscatter, then the pixel was labeled as emergent.

If a pixel belongs to TM class aquaculture and lowest backscatter, then the pixel was labeled as open water.

If a pixel belongs to TM class aquaculture and medium backscatter, then the pixel was labeled as aquaculture.

Rules such as the above mentioned have been used to combined the results of the classification of two kinds of data and accuracy improvements have been made (Figure 1).

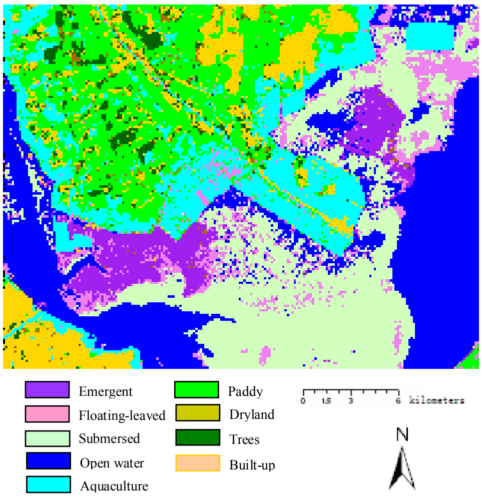

Figure 4 Results of SAR-based rule Processing

The accuracy of classification using tree classifier was 83.81%, kappa coefficient was 0.8164, while the accuracy of classification by the combination of two kinds of data was 92.3%, and Kappa coefficient was 0.8932.

V. CONCLUSIONS AND FUTURE WORK

This research has shown that the combination of optical remotely sensed data and radar data is promising was for the solution of confusion between upland categories and wetland categories. Compared with the classification of only optical remotely sensed data, the integration of optical-based data with radar SAR data can effectively improved the accuracy of classification. Next, Envisat ASAR, acquired on the different growth stage of vegetation, will be used for further separation of dryland from paddy rice.

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