Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia Environmental Sciences 10 (2011) 1726 – 1731
Procedia Environmental Sciences

2011 3rd International Conference on Environmental Science and Information Application Technology (ESIAT 2011)

Landscape and Water Quality Change Detection in Urban Wetland: A Post-classification Comparison Method with IKONOS Data

ZHOU Huiping [1], JIANG Hong [2], HUANG Qinghua [3]

1Nanjing institute of environmental science, ministry of environmental protection, Jiangwangmiao Street 8, Nanjing 210042, China
2International institute for earth system science, Nanjing University, Hankou Road 22, Nanjing 210093, China
3Jiangxi provincial water conservancy planning and designing institute, East-beijing Road, Nanchang 330029, China
ci_hui@yahoo.cn

Abstract.

Concerns are growing in recent years about wetland resources and their changes, especially in coastal urban areas. This study used IKONOS images to map an urban wetland and detect the changes of land-cover as well as general water quality with post-classification comparison method. The results indicated that an Optimal Iterative Unsupervised Classification (OIUC) method produced overall accuracy over 83% in land-cover classification. A decrease of 7.08% in water surface area and an increase of 31.35% in vegetations area had been found in the wetland for a period of 3 years. Also about 21.6% of the water was observed to change to worse quality. It shows IKONOS image is advanced in studying changes of an urban wetland at a local scale. Ground surveys that coinciding with satellite data and new classification algorithms are needed to achieve better results

Selection and/or peer-review under responsibility of Conference ESIAT2011 Organization Committee.

Keywords: IKONOS, urban wetland, change detection, optimal iterative unsupervised classification

Introduction

Wetland play an important role in offering wildlife habitat and tourist destinations, as well as providing other services such as agricultural production, floodwater retention, fisheries, and also functioning as important nutrient cycling capacity for maintaining water quality [1-3]. The concerns of damage and loss of wetlands as a result of rapid urbanization, especially in urban regions, have been growing in recent years.

Selection and/or peer-review under responsibility of Conference ESIAT2011 Organization Committee.
doi:10.1016/j.proenv.2011.09.271

Monitoring the change of wetland water quality as well as landscape are increasingly central objectives of management agencies. However, conventional methods including field sampling and surveying are time-consuming and costly [4]. Remote sensing is effective in mapping and monitoring the wetland conditions, and thus enables derivation of cost-effective solution for wetland management [4, 5]. While in urban area which with highly fragmented landscapes, the characteristic spatial scale of water bodies and vegetation are often much smaller. High spatial resolution remote sensing data then is necessary in mapping complex land cover and land use, and monitoring the changes of wetland system within an urban context at a local scale.

The IKONOS satellite collects images at 1-m resolution in panchromatic band and at 4-m resolution in four multi-spectral bands, which has become a popular tool in the study of agriculture [6], urban environmental quality [7], forest study [8, 9], land and water resource [10], etc. However, studies focused on wetland system in a local scale area scarce.

The objectives of this research were to (1) detect the changes of an urban wetland over a specified time period using post-classification comparison approach with IKONOS image; (2) develop a rapid way in mapping wetland water quality and detecting water quality changes.

Methodologies

Study Site. Xixi wetland located in the downtown of Hangzhou, China, lies between 120°0′26″-120°9′27″ E and 30°3′35″-30°21′28″ N and covers an area of about 11 square kilometers (Fig. 1). It consists of rivers, brooks, swamps and lakes. Xixi is crisscrossed by six rivers and dotted with many piers, docks and fish-scale-shaped ponds, forming the unique wetland landscape. It also boasts abundant water-land vegetations and wild animals.

Fig. 1 Location of Xixi Wetland in China

Data. Two cloud-free IKONOS images covering the whole Xixi Wetland area acquired in June 2003 and January 2006 were selected, for the difficulties to find out two images well matched in season. All images included four multi-spectral bands and a panchromatic band. The projection system was Universal Transverse Mercator (UTM) Zone 51and the Spheroid and Datum was WGS 84.

Field sampling work was conducted on January 30, 2007. The field conditions and the results were assumed to be similar and comparable to those in January 2006 as there was little change between the two stages as we learned. The image characteristics and the corresponding wetland cover types were examined and qualitative descriptions were recorded for the purposes of better image classification. Water samples from 16 stations, which sampled based on good professional judgment and previous information, were analyzed in laboratory for physicochemical parameters as secchi disk transparency

(SDT), turbidity, conductivity, dissolved oxygen (DO), chemical oxygen demand (COD), biological oxygen demand (BOD) and suspended solid (SS). Other background dada including limited ground survey data, land use map and TM image in September 2003 were also acquired as reference data.

Image Processing. The 2003 image was rectified with reference to the recent 2006 image using ERDAS Imagine 9.0 software. A two-order polynomial transformation model and a cubic convolution resample method were used and RMSE fell within 0.2-0.6 pixels. As IKONOS image is advanced in visual interpretation due to its high spatial resolution, a pan-sharpened multi-spectral image was produced for better interpretation and the subsets for the study area were created finally with the boundary of Xixi Wetland.

A classification procedure was performed with the two images before post-classification comparison change detection. As it was difficult and expensive to obtain a suitable training set when large homogenous sample size and enough multi-temporal "ground truth" data were not available, an Optimal Iterative Unsupervised Classification (OIUC) method was used here instead of supervised classification to overcome the limitations of unsupervised way [11, 12]. The OIUC includes three steps: (1) development of reference datasets upon which to base the satellite image classification; (2) optimal iterative classification using ISODATA clustering; and (3) post-classification treatment. This method has been tested as an efficient and cost-effective alternative that yields high quality results for relatively large geographic areas[13, 14]. 40 clusters were initially produced here and compared with the reference images and other datasets. Spectral classes that agreed with observed classes using reference image were considered good matches, and then labeled and removed from further consideration. Spectral classes that were less clear were put back into the remaining pixel pool and rerun again. This was repeated as many times as needed to assign our final classification results. As a great number of individual class pixels were produced in the classification process, before forming the final result, we removed all pixel clusters with a threshold of 3×3 pixels using CLUMP and ELIMINATE tools.

However, there were confusions among specific ground features which had similar spectral signatures. For example, the shadows of buildings and roofs with asphalt were confused with open deep water. Agricultural land with green crops was similar to other green vegetation according to their spectral characteristics. Marshs or mudflats were also confused with some watered cropland. In the winter image of 2006, the perished vegetations were confused with bare lands. By visual interpretation with reference to the pan-sharpened color composite images according to their shape, color, texture and other ground reference data, the confused pixels could be easily separated and edited manually.

Results and Discussions

Classification and Change Detection Accuracy. According to the landscape characteristics in Xixi, we categorized it into six classes: (1) water body (permanent rivers, lakes, and ponds), (2) wetland (marsh and mudflat), (3) vegetation (natural and planted), (4) agricultural (paddy field and dry cropland), (5) developed (construction and road), (6) others (bare land and wasteland). Similar land cover types were grouped together under these classifications.

The overall classification accuracies for 2003 and 2006 were 83.2% and 86.3%, with Kappa statistics of 0.793 and 0.828. For individual classes, user's and producer's accuracies ranged from 60% to 96%, and 65.8% to 100%, respectively. A higher overall classification accuracy and kappa coefficient showed a better performance with the 2006 image. It is understandable that compared with the limited second-hand ground survey and land use data of 2003, the field work in January 2007 was helpful to better interpret the image of January 2006. For each land-cover type, the lower accuracy for "water body" of 2003 may be attributed to the random selected reference pixels which fell in the border of the open water. The accuracy for "agricultural" and "developed" was relative higher because some pixels were reclassified manually by visual interpretation after unsupervised classification. The change detection accuracy was 71.8% for 2003-2006, evaluated by simply multiplied the individual classification accuracies.

Land-cover Change. By comparing the classified images, a detailed land-cover type transformation matrix was calculated and described in Table 1. It showed that the "water body" and "wetland" areas were slightly decreased by 7.08% and 12.53%, respectively. This change could have two explanations. The first was that the compared images were acquired in different seasons (June 2003 and January 2006). Water level in some ponds which are separate from fluid water body is relative low in winter for infrequent precipitation. Some ponds, originally with lower water levels, transformed to marsh or dry land. However, some fluid rivers are little affected by weather condition as the water level is controlled artificially for landscape demand. Furthermore, in later 2003, the "Xixi Wetland Protection Project" initiated. Some protection practices filled and leveled up some ponds and wetlands. In fact, some shallow or narrow water areas had also been dredged up to be wide rivers, which conversely increased the "water body" area. It appeared that the overall decreased areas exceeded the increased areas. As for "vegetation" areas, an obvious increase was observed (31.35%). Under the stress of environment degradation and the slogan of protection, destroying the vegetation was forbidden in this region in recent years. Moreover, the project of "National Wetland Park" contributed to the increase of vegetation area by planting additional vegetation. For the purpose of protecting the natural landscape and water quality, agricultural land in the wetland area had been withdrawn extensively, which resulted in a large decrease of "agricultural" areas and also an increase of "vegetation" areas. However, some agricultural land also transformed to bare or waste land without proper utilization or management.

Table 1 Transform matrix of land-cover classes in Xixi Wetland from 2003 to 2006

		Area of 2006 (ha.)						Sum of 2003
		Water body	Wetland	Vegetation	Agricultural	Developed	Others	
Area of 2003 (ha.)	Water body	336.52	51.68	50.69	1.57	11.36	7.25	459.07
	Wetland	35.12	26.25	68.81	3.94	8.00	4.61	146.73
	Vegetation	27.53	30.36	154.70	8.74	17.88	9.28	248.49
	Agricultural	7.66	4.54	26.36	42.94	12.43	3.93	97.86
	Developed	13.30	12.47	19.63	0.82	66.25	5.44	117.91
	Others	6.43	3.04	6.21	0.60	2.20	0.91	19.39
Sum of 2006		426.56	128.34	326.40	58.61	118.12	31.42	1089.45

Water Quality Change. As known, SDT, Turbidity and SS are the most consistently collected water quality indicators that can be derived from spectral reflectance data. Previous studies have shown a strong correlation between the ground observation of water clarity and the responses in blue and red bands of Landsat image[15, 16]. IKONOS imagery has four multi-spectral bands similar to Landsat TM 1-4 bands, so we can also assess water quality by analyzing its spectral information. Then, general water quality could be assessed qualitatively by image classification as limited ground reference data concurrently with the remote sensing data was available to develop quantitative model. We masked out terrestrial features and creating a water-only image of 2006. Unsupervised classification was performed on the water-only image and three different spectral classes were generated. We defined the three classes as 'Better', 'Medium' and 'Worse' to represent three different water quality, that is, the class with higher reflectance (brighter pixels) showed worse water quality, while a lower reflectance (darker pixels) showed better water quality. In order to relate the spectral classes to different water quality and test the ability of unsupervised classification to separate and group the pixels with different water quality, water quality classes and corresponding range of indicator values were defined according to the previous observed ground data (Table 2). Then, the sampled water quality data were grouped and compared with the image classification results for validation by matching their locations.

Table 2. Range of indicator values for different water quality classes.

Class	SDT (cm)	Turbidity (NTU)	SS (mg/l)
Better	>55	<7	<10
Medium	35-55	7-10	10-18
Worse	<35	>10	>18

Water quality of 16 sampling sites was assigned for three indicators according to the criteria defined in Table 2. For all indicators, water quality classes were completely consistent with each other at 7 sites (Table 3). Other sites also showed good consistency between two indicators except for site 12. By locating the 16 sites on the classified image, we found the spectral classes at 4 sites were consistent with the results from other three indicators, and 5 sites were consistent with two indicators, while other sites did not show a good consistency. Even though, it indicated that the spectral classification could generally identify different water quality.

Table 3. Water quality classes reference to SDT, turbidity, SS and spectral classification results.

Sites	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
SDT	W	M	M	B	M	M	W	M	B	B	B	B	B	M	W	B
Turbidity	W	B	M	B	W	M	W	W	M	B	B	W	M	M	W	B
SS	W	M	M	B	W	M	W	M	M	M	B	M	M	W	M	B
Spectral	W	W	M	B	W	W	M	W	M	B	M	M	M	M	M	B

B-Better, M-Medium, W-Worse

The image of June 2003 was processed and three water quality classes were assigned in the same way because no ground monitoring data was available for 2003. We compared the water quality changes from 2003 to 2006 on the supposing that the water in same quality classes between the two images had similar reflectance characteristics and similar range of indicator values. Because the area of water surface had changed over the 3 years, we discussed the water quality change only in the unchanged area. A cross-tabulation analysis (Table 4) showed that about 21.6% of the water area changed from better and medium to worse class, while another 13.3% changed from medium and worse to better class. The area with worse quality increased 75% from 2003 to 2006.

Table 4. Transform matrix of each water quality classes from June 2003 to January 2006

		Area of 2006 (ha.)			Sum of 2003
		Better	Medium	Worse	
Area of 2003(ha.)	Better	58.75	62.79	25.37	146.91
	Medium	31.01	64.21	47.19	142.41
	Worse	13.58	23.60	10.01	47.19
Sum of 2006		103.34	150.60	82.57	336.51

The water quality map of 2006 (Fig. 2B) showed that the water in main rivers were the worst. This mainly attributed to the disturbance from anthropic activities, such as water traffic and tourism. Water in the most ponds showed relatively better water quality, it is because most of the ponds were not accessible while some ponds were polluted by aquiculture. It should be point out that there were confusions between shallow water and high turbidity water, because the high bottom reflectance from shallow ponds were similar with the reflectance from turbidity water. We ignored this problem here, for the depth and water quality information was not available in this paper. A detailed survey in large area was needed to improve water quality classification in further study.

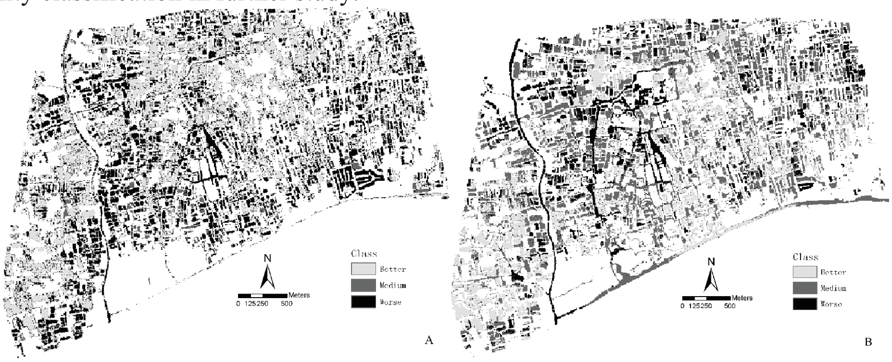

Fig. 2 Water quality map of June 2003 (A) and January 2006 (B)

Conclusions

IKONOS image is advanced in studying an urban wetland at a local scale. An OIUC method, combined with visual interpretation and post-classification processing, could also yield high classification accuracy. A post-classification comparison method was also demonstrated as an efficient way to detect the wetland changes. Unsupervised classification is also a useful tool to quickly assess general water quality when detailed data is not available. Ground surveys that coinciding with satellite data and new classification algorithms are needed to achieve better results. The results of this paper also showed that Xixi had undergone tremendous landscape changes in those three years. Extended and periodic monitoring work is necessary in the future for better protection and utilization of the urban wetland resources.

References

[1] B. R. M. Rao, R. S. Dwivedi and S. P. S. Kushwaha: International Journal of Remote Sensing. Vol. 20 (1999), p. 2509-2517.

[2] J. T. A. Verhoeven, B. Arheimer, C. Yin, and et al.: TRENDS in Ecology and Evolution. Vol. 21 (2006), p. 96-103.

[3] J. J.Kashaigili, B. P. Mbilinyi, M. Mccartney and et al.: Physics and Chemistry of the Earth. Vol. 31 (2006), p. 967-975.

[4] P. Shanmugam, Y. Ahn and S. Sanjeevi: Ecological modeling. Vol. 194 (2006), p. 379-394.

[5] A. Cózar, C. M. García, J. A. Gálvez and et al.: Ecological Modelling. Vol. 186 (2005), p. 29-41.

[6] A. Bannari, A. Pacheco, K. Staenz and et al.: Remote sensing of environment. Vol. 104 (2006), p. 447-459.

[7] J. Nichol and M. S. Wong: Landscape and urban planning. Vol. 73 (2005), p. 49-58.

[8] P. S. Thenkabail, E. A. Enclona, M. S. Ashton and et al.: Remote sensing of environment. Vol. 90 (2001), p. 23-43.

[9] F. Kayitakire, C. Hamel and F. Defourny: Remote sensing of environment. Vol. 102 (2006), p. 390-401.

[10] K. E. Sawaya, L. G. Olmanson, N. J. Heinert and et al.: Remote sensing of environment. Vol. 88 (2003), p. 144-156.

[11] J. Cihlar: International Journal of Remote Sensing. Vol. 21 (2000), p. 1093-1114.

[12] H. Lachowski, P. Maus, M. Golden and et al.: Guidelines for the use of digital imagery for vegetation mapping (US Department of Agriculture, Forest Service, Engineering Report EM-7140-25, 1996).

[13] H. Jiang, S. Liu, P. Sun and et al.: Canadian Journal of Remote Sensing. Vol. 30 (2004), p. 743-763.

[14] H. Jiang, J. R. Strittholt, P. A. Frost and et al. Remote sensing of environment. Vol. 91 (2004), p. 320-331.

[15] S. M. Kloiber, P. L. Brezonik, L. G. Olmanson and et al.: Remote Sensing of Environment. Vol. 82 (2002), p. 38-47.

[16] S. M. Kloiber, P. L. Brezonik and M. E. Bauer: Water Research. Vol. 36 (2002), p. 4330-4340.