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Land cover change in Ningbo and its surrounding area of Zhejiang Province, 1987~2000*

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Abstract: Ningbo and its surrounding area is the forefront in the rapid economic development in the Yangtse delta, and the main production area for food supplies, cotton, edible oil and hemp; and at the same time, is the main area for wetland protection in Zhejiang Province. Our objectives were to quantify land cover change in Ningbo and its surrounding area from 1987 to 2000 and to analyze the causative factors of the change. Using 30-m resolution Landsat TM/ETM+ data and maximum likelihood classification method, we classified the study area into six land cover types: forest, agriculture, urban, freshwater, seawater and bottomland. The research results showed that significant changes in land cover occurred in the study area, and that agriculture and urban land cover change dominated most of the land cover change and were main causes for the changes of other types with human activities, such as urbanization, industrialization, etc. being the main factor while it was not very obvious whether climatic conditions have any role in the land cover changes. Agriculture, bottomland and other nature dominated land cover types are undergoing significant changes due to industrialization and urbanization, which threaten the stabilization of the environment. The study conclusion called for finding reasonable ways to solve the problems between land cover change and land use.

Key words: Land cover change, Maximum likelihood classification, Landsat TM/ETM+, Remote sensing, Ningbo
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INTRODUCTION

Land use and land cover change (LUCC) has become an increasingly important aspect of global environmental change and is a multi-disciplinary subject where geophysicist, bio-physicists and socio-economists meet one another. Land cover is an expression of human activities and, as such, changes with changes in land use and management (Louisa and Antonio, 2001), and land cover change could be regarded as change in biotic diversity, actual and potential productivity, soil quality, run-off and sedimentation rates (Steffen *et al.*, 1992).

There are many causative factors of land cover change, including factitious factors and natural factors, with land use being the most important factor (Li, 1996; Ramadan *et al.*, 2004). Unreasonable land use and improper water resource management were the main reasons for land cover change in Taoer Cachment area (Xia *et al.*, 2004). The land cover change in Bashang area, Hebei Province, resulted from population explosion and excessive land use (Zhou *et al.*, 2004). Great climate change was the main cause of land cover change and desertification in Minqin County, Gansu Province (Wang *et al.*, 2004). Land cover change in upper Barataria Basin estuary, Louisiana can be ascribed to the existence of numerous oil, gas, and drainage canals throughout the basin, and to weather conditions (Nelson *et al.*, 2002).

Ningbo and its surrounding area is the forefront in the rapid economic development in the Yangtse delta, and the main production area for food supplies, cotton, edible oil and hemp and at the same time, is the main area for wetland protection in Zhejiang Province. Coastal wetland is an important field for

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bird inhabitation, wintering and breeding. For example, wetland of Sanbei, Cixi is an area for bird protection.

Since the early 1980s, remote sensing images and geographic information systems (GIS) are being used to identify and analyze land use and land cover changes. The results provide researchers with information enabling them to make rapid decisions using recent data (Ricketts, 1992). A number of researches were carried out using various methodologies and algorithms to obtain land cover change information from different remotely sensed datasets (Tateishi and Kajiwara, 1991; Lichtenegger, 1992; Muchoney and Haack, 1994; Lambin, 1996; Sailer *et al.*, 1997). Researchers used historical data available from satellite platforms like the Landsat Multispectral Scanner (MSS). It is necessary and wise to use Landsat TM and Landsat MSS data to analyze the long period changes (Hashiba *et al.*, 2000).

Our objectives were to quantify land cover change in Ningbo and its surrounding area from 1987 to 2000 and to analyze the factors that caused the change. Land cover of Zhejiang Province can be classified into 8 primary types and 26 secondary types according to the different purposes of land use, different characteristics of management and different patterns of land use (Yu and Wang, 1987). We classified the research area into four primary types: forest, agriculture, urban, water area, and then classified the water area into three secondary types: seawater, freshwater, and bottomland. All these types of land cover can be divided into another two types: human dominated land covers (agriculture, urban) and nature dominated land covers (forest, water area). We obtained Landsat TM/ETM+ data from the China Remote Sensing Satellite Ground Station, using a supervised image classification approach, and classified each scene into 6 types: forest, agriculture, urban, freshwater, seawater and bottomland. The final result showed that different land cover types have different change trends.

STUDY AREA

The study area, 4673.59 km^2, is among the key developing areas open to the outside world in China's coastal economic zone, and is situated in the eastern part of Zhejiang Province on the southern shore of the Hangzhou Bay (121°05′~121°40′E, 29°32′~30°15′N) (Fig.1), with semi-tropical monsoon climate, hot summer and cool winter, precipitation with marked seasonal variations, annual mean temperature of 16.3 °C based on available meteorological data, forest vegetation consisting mainly of conifers, broadleaf trees and bamboo, main crops of barley, paddy rice, rape and cotton, major source of water supply being rainfall, and estimated annual precipitation of 1418 mm (Hua and Zhu, 2000).

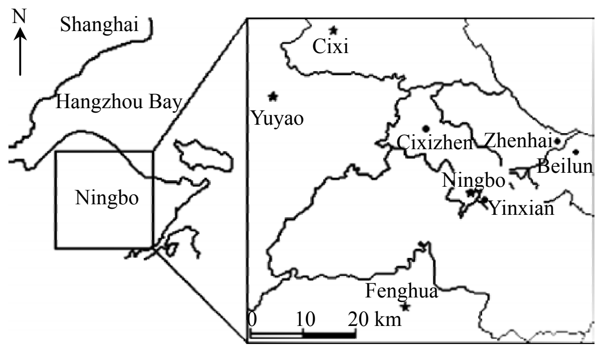


Fig.1 Study zones sketch map showing three weather stations: Zhenhai, Yuyao and Yinxian

METHODS

Satellite image data and preprocessing

The data we used in this study were comprised of two 30-m resolution Landsat TM/ETM+ scenes covering the total research area on 18 May 1987 (Landsat TM) and 14 June 2000 (Landsat ETM+). Each image was enhanced using linear contrast stretching and histogram equalization to improve the image and help identify ground control points in the rectification. The two scenes were geometrically rectified to a digitally scanned, 1:100000 scales topographic map and transformed to Transverse Mercator. A nearest-neighbour algorithm was used to perform the resampling procedure and the Image-to-Map registrations, which yielded a root-mean-square error of 0.90 pixels for all data.

Supervised image classification

Remote sensing has become an inevitable tool for resource inventory and environmental monitoring at local, regional and global scales during the last thirty years. It has become an integral part of information technology and provides solutions to facilitate sustainable development of natural resources and conservation of environment. Applications oriented research in many countries has led to operational and commercial use of this technology in many fields (Ramadan *et al.*, 2004).

There are many land cover classification methods such as maximum likelihood (ML), artificial neural networks (ANN), decision tree (DT), etc. Choice of a classification algorithm is generally based on a number of factors, among which are software availability, ease of use, and performance. The ML procedure is, for many users, the algorithm of choice because of its ready availability and its not needing extended training process. ANN is now widely used by researchers, but their operational applications are hindered by the need of the user to specify the configuration of the network architecture and to provide values for a number of parameters, both of which affect performance. DT is computationally fast, makes no statistical assumptions, and can handle data represented on different measurement scales. Comparing the classification accuracy of different methods, we found DT performed better than other classifiers (Friedl and Brodley, 1997; Rogan *et al.*, 2002; Pal and Mather, 2003). However, ML is still the most commonly used method for land cover and land use change analysis due to its sententiousness and practicality.

Each band of Landsat TM/ETM+ reflects specific information about the earth's surface, and the combination of different bands can increase the extraction accuracy of specific types, but it is not necessarily true for multi-information extraction. The overall accuracy of three TM bands combination image is lower than the image of TM bands 1~5 and 7 combined with Soil-adjusted Vegetation Index (SAVI) when diversity classes should be distinguished (Stefanov *et al.*, 2001). In this study, we used TM/ETM+ bands 1~5 and 7 combined with a vegetation index (NDVI) layer in place of band 6 because of its coarse resolution. The NDVI (Normalized Difference Vegetation Index) values indicate the amount of green vegetation present in the pixel, higher NDVI values indicate more green vegetation. It uses the standard algorithm:

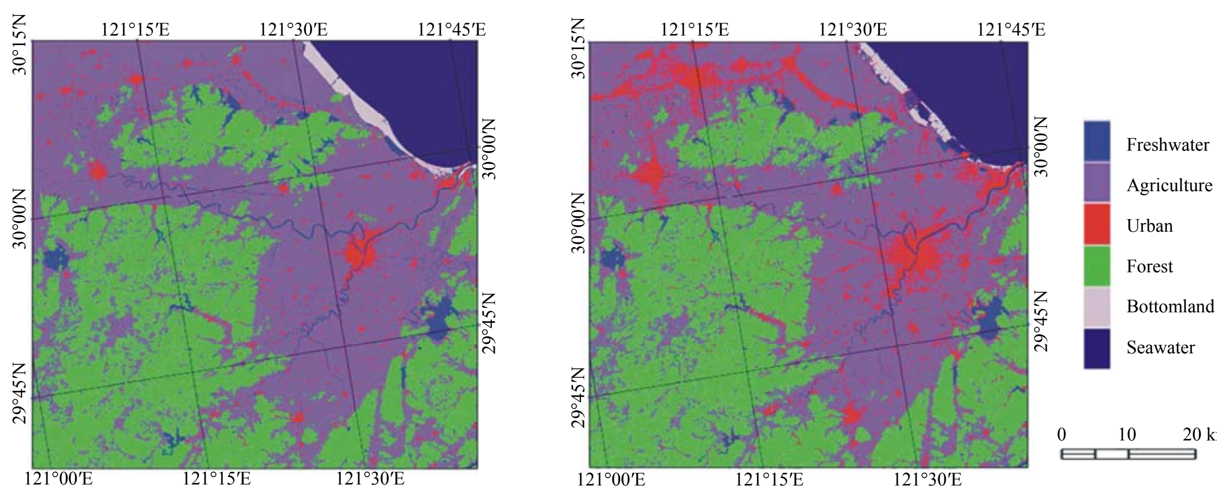
$$NDVI = (NIR - VIred)/(NIR + VIred),$$

where *NIR* (near infrared)=Band 4; *VIred* (visible red)=Band 3 (Jensen, 1986). As the *NDVI* is a band ratio, it can minimize shadow effects on subsequent classification.

Because false color image results from a band combination of 7, 4 and 3, it is easy to distinguish the land cover types by visual interpretation. We used this bands combination method to choose reasonable sample data for each land cover type. Then, a supervised signature extraction with the maximum likelihood algorithm was employed to classify each scene, and we got two classified land cover images (Fig.2).

Accuracy assessment

It is important that the quality of thematic maps derived from remotely sensed data be assessed and expressed in a meaningful way. This is important not



(a) (b)

Fig.2 Classified land cover images in 1987 (a) and in 2000 (b)

only in providing a guide to the quality of a map and its fitness for a particular purpose, but also in understanding error and its likely implications, especially if allowed to propagate through analyses linking the map to other datasets (Arbia, *et al.*, 1998; Veregin, 1994). Although classification accuracy assessment is now widely accepted as a fundamental component of thematic mapping investigations (Cihlar, 2000; Cohen and Justice, 1999; Congalton, 1994; Justice *et al.*, 2000; Merchant *et al.*, 1994), accuracy is a difficult property to measure and express.

Congalton (1994) identified four major historical stages in accuracy assessment. In the first, accuracy assessment was based on a basic visual appraisal of the derived map. The second historical stage was characterized by an attempt to quantify accuracy more objectively. In this, accuracy assessment was based on comparisons of the areal extent of the classes in the derived thematic map relative to their extent in some ground or other reference dataset. The third stage in the history of accuracy assessment involved the derivation of accuracy metrics based on a comparison of the class labels in the thematic map and ground data for a set of specific locations. Finally, the fourth stage in the history of accuracy assessment is a refinement of the third in which greater use of the information on the correspondence of the predicted thematic map labels to those observed on the ground is made. This stage has the confusion or error matrix at its core and uses this to describe the pattern of class allocation made relative to the reference data. In these methods of accuracy assessment, the method of the fourth stage was the most commonly used in the past.

A meaningful accuracy assessment clearly requires that the reference data should be accurate (Giles, 2001), and it is the optimal assessment for classification accuracy using ground truth image or data, but because of the large size of the study area and historical data, use of ground truth image was not possible (Jensen *et al.*, 1995). However, the truth image can be another classified image, or an image created from actual ground truth measurements. Using confusion matrix the classification accuracy can be shown by comparing the classified image with ground truth information. To estimate the classification accuracy in this study, we developed two confusion matrices from the 2000 classification using two different reference data. For the first assessment, we used a 13 March 2001 Landsat ETM+ scene (30-m resolution) as ground truth information covering 100% of the study area and obtained overall classification accuracy of 87.6% by using 500 randomly generated points (Table 1). For the second assessment, we used a 12 October 2003 SPOT-5 scene (10-m resolution) as ground truth data covering approximately 23.5% of the study site, the classified map of 2000 was subset to match this scene. Two hundred and twenty seven points were randomly generated to represent 23.5% of the total area, the overall classification accuracy of this assessment was 84.14% with all the classes being more than 70% accurate. But what is the reasonable accuracy for image classification? Many researchers tried to answer this question with target accuracy thresholds specified (Congalton *et al.*, 1993; Smits *et al.*, 1999; Thomlinson *et al.*, 1999). However, there was no uniform standard now on what is the reasonable accuracy. Typically, the specified requirements take the form of a minimum level of overall accuracy, expressed numerically by some index such as the percentage of cases correctly allocated, and a desire that each class to be classified to comparable accuracy. For example, Thomlinson *et*

Table 1 Confusion matrix for comparison between 2000 classification and reference classified image of 2001

Class##	Ground truth (pixels)#						The total points of each class
	Forest	Agriculture	Urban	Freshwater	Seawater	Bottomland	
Forest	159*	20	1	0	0	0	180
Agriculture	6	194*	13	1	0	0	214
Urban	0	7	36*	4	0	0	47
Freshwater	0	1	3	16*	0	0	20
Seawater	0	0	0	3	32*	2	37
Bottomland	0	0	1	0	0	1*	2
The total ground truth (pixels)	165	222	54	24	32	3	500

*The number of correctly classified pixels for each land cover; #The reference classified image of 2001; ##The classified image of 2000 *al.*(1999) set a target of overall accuracy of 85% with no class less than 70% accurate. In this study, we think that an overall accuracy of more than 80% with each class being more than 70% accurate is as high accuracy. As no reference imagery was available for the 1987 classification, however, given the high accuracy of the classification in 2000, we assumed that the identical techniques used in the development of the classification in 1987 would have produced comparable accuracy (Nelson *et al.*, 2002).

Results

During the investigation period, for the primary types of land cover, distinct changes have occurred: urban area increased, agricultural land, forest and water area all decreased. For the secondary types, each of them decreased over time. Table 2 shows the percentage of each type in 1987 and 2000.

Table 2 Percentage of each type in 1987 and 2000

Land cover types	Percent (%)	
	1987	2000
Forest	37.93	37.48
Agriculture	47.79	44.14
Urban	2.99	8.43
Freshwater	3.02	2.21
Seawater	7.30	7.03
Bottomland	0.97	0.71

Among all the types, there were small changes in total human dominated land covers and in total nature dominated land covers. The former increased while the latter decreased. However, there were different change trends within these two types. In 1987, agriculture land cover made up 94.116% of the human dominated land, but only approximately 83.964% by 2000. Urban land cover made up 5.884% of the human dominated land in 1987 and increased to approximately 16.036% by 2000. Regarding the nature dominated land cover, it can be stated that forest and water area decreased throughout the entire study period (Table 3).

Many methods of change detection have been used to study land cover change (Lambin and Ehrlich, 1997; Mas, 1999; Singh, 1989), but by far, the most popular method was the postclassification comparison. In this study, to examine in more detail how land cover changed, we calculated a transition matrix

Table 3 Percent and area of land cover occurring within human dominated land cover types and within nature dominated land cover types in the study period

Land cover types	Percent (%)		Area (km^2)	
	1987	2000	1987	2000
Urban*	5.884	16.036	2373.070	2456.630
Agriculture*	94.116	83.964		
Forest**	77.056	79.019	2300.530	2216.920
Freshwater**	6.143	4.661		
Seawater**	14.834	14.831		
Bottomland**	1.967	1.488		

*Human dominated land cover types; **Nature dominated land cover types

(Table 4). We can see two land cover conversions were most prominent in this table: the conversion from agriculture to urban and the conversion from seawater to bottomland. Then, we developed four variables to examine the extent of land cover change, including T_a (the total area), C_a (the changed area), C_e (the change extent) and C_r (the annual change rate). All these variables can be described by the following formulas:

$$C_a=T_a(t_2)-T_a(t_1);\ C_e=C_a/T_a(t_1);\ C_r=C_a/(t_2-t_1),$$

where t_1 and t_2 represent the beginning and ending time of the investigation, in this study, t_1=1987, t_2=2000.

Tables 5 and 6 show detailed information on the change of each type across the whole study period. The largest annual change rate was an increase of 19.56 km^2/a for urban land cover, the only type that gained area through time. Freshwater showed a net loss with largest annual change rate of 2.92 km^2/a among the secondary types. Though the annual change rate of bottomland is only 0.94 km^2/a, it has the second largest change extent.

DATA ANALYSIS

During the study period, land cover in the study area changed quantitatively and spatially. We explored each type in detail below.

Agriculture accounting for the largest proportion of the total study area, decreased at 13.13 km^2/a. The agriculture area lost was converted into urban area, with all these changes centering around the towns.

Table 4 Area (km^2) of land converted from one land cover to another between 1987 and 2000#

Land cover types in 2000	Land cover types in 1987					
	Urban	Forest	Agriculture	Freshwater	Seawater	Bottomland
Urban	112.22*	5.42	252.10	13.39	2.93	7.82
Forest	0.73	1596.28*	153.90	1.04	0.00	0.00
Agriculture	22.84	169.96	1814.28*	47.42	0.05	8.08
Freshwater	2.42	1.13	12.23	78.39*	3.21	5.93
Seawater	0.02	0.00	0.09	0.88	322.63*	5.17
Bottomland	1.40	0.02	0.73	0.20	12.41	18.25*

#For example, the area of agricultural land present in 1987 that was converted to urban land in 2000 is 252.10 km^2; *The area of no change in the study period

Table 5 T_a (km^2), C_a (km^2), C_e (%), C_r (km^2/a) for each primary type

Primary types	T_a(1987) (km^2)	T_a(2000) (km^2)	C_a (km^2)	C_e (%)	C_r (km^2/a)
Forest	1772.69	1751.80	−20.89	−1.18	−1.61
Agriculture	2233.42	2062.69	−170.73	−7.64	−13.13
Urban	139.65	393.94	254.29	182.10	19.56
Water area	527.84	465.12	−62.72	−11.88	−4.82

Positive numbers are gains in land cover area and negative numbers are losses in land cover area

Table 6 T_a (km^2), C_a (km^2), C_e (%), C_r (km^2/a) for each secondary type

Secondary types	T_a(1987) (km^2)	T_a(2000) (km^2)	C_a (km^2)	C_e (%)	C_r (km^2/a)
Freshwater	141.33	103.33	−37.99	−26.89	−2.92
Seawater	341.27	328.79	−12.48	−3.66	−0.96
Bottomland	45.24	32.99	−12.24	−27.07	−0.94

Positive numbers are gains in land cover area and negative numbers are losses in land cover area

The most marked change occurred to the urban land cover, which changed by 182.10% at 19.56 km^2/a, expanded around the towns more or less radially and reduced the agriculture area directly. Fig.3 shows the change of urban land cover about a region of 10 km×8 km around the central region of Ningbo from 1987 to 2000, the regions of grey color in the map represent the urban land cover in 1987 and black color represent the urban land cover in 2000.

In general, weather conditions were the main causative factors of changes on the nature dominated land cover. In large-scale study of land cover changes, the effect of weather conditions are often predominant (Li *et al.*, 2000). Fig.4 shows the change of annual air temperature and annual rainfall in the study area from 1987 to 2000 measured at the three weather stations in Fig.1. The annual air temperature definite changed during the time period and rose unsteadily. We separated the time period of the annual rainfall into two sub-periods: one from 1987 to 1993, the other from 1994 to 2000, and then calculated the mean annual rainfall of these two periods, which showed that the annual rainfall rose unsteadily too (Table 7).

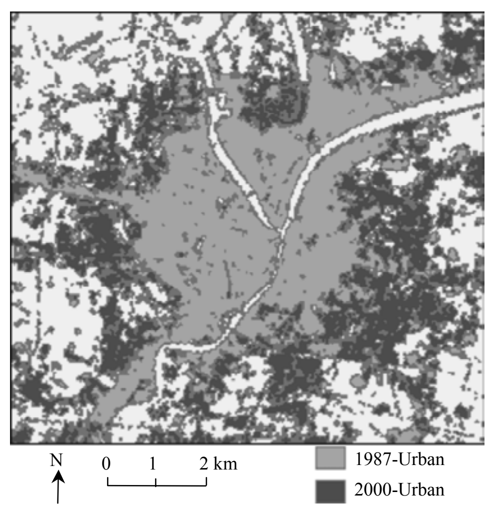


Fig.3 Map of urban land cover change around the central region of Ningbo from 1987 to 2000

Although such changes occurred in weather conditions, it was not very obvious whether climatic conditions caused the land cover change in the study area.

Forest accounted for 1/3 of the total study area, but changed little. In the study time period, it decreas-

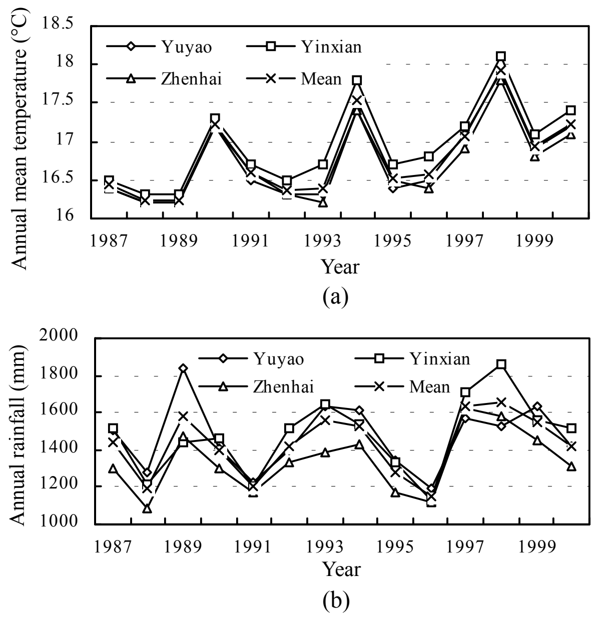


Fig.4 Annual air temperature (a) and annual rainfall (b) reported by three weather stations and their mean value during the study time

Table 7 Mean annual rainfall in the two sub-periods (Unit: mm)

Time step	Yuyao	Yinxian	Zhenhai	Mean
1987~1993	1470.5	1427.8	1294.0	1397.4
1994~2000	1473.4	1521.6	1381.0	1458.7

ed by 20.89 km^2, and mainly this change was the expansion of urban land cover and agricultural land in the mountainous areas.

During the study time, bottomland decreased at 0.94 km^2/a, and greatly changed its spatial position for seashore polder resulted in a decrease of the seawater area, which was converted into agriculture, partly into urban area.

From 1985 to 2000, great change of land cover occurred in Shanghai, on the northern shore of Hangzhou Bay. Urban land cover and other architectural areas were increasing by 4.46% and 4.02% per year respectively, agriculture land cover and other use of land were decreasing by 0.55% and 1.70% per year, and bottomland area was decreasing by 4.58% per year, while few changes occurred on forest land cover (Hong *et al.*, 2004). Regarding land cover change of Shanghai and the study area, we could see similar land cover change in these two areas during the study time. Land cover change of the study area has good territorial representation characteristics.

CONCLUSION

In the present study, an integrated approach of remote sensing, GIS and statistics was used for land cover change detection. Results revealed notable changes in the study area, especially for agricultural land and urban area. Agriculture and urban land cover change dominated most of the land cover change in this area and were the main causes for the change of other types. Compared with the neighboring area of Shanghai, we found that the change from agriculture to urban land was the most prominent land cover change in the study area, and can be considered as the main land cover change throughout the Yangtse delta. The main reasons for land cover change are human activities, such as urbanization, industrialization, etc., while it was not very obvious whether climatic conditions have any role in the land cover change. Agriculture, bottomland and other nature dominated land cover types are undergoing significant change due to industrialization and urbanization, which threaten the stabilization of the environment, so reasonable measures are needed in this area to keep harmonious relationship between human activities and environment, and further study should lay emphasis on territorial model construction for analysis and forecast the future land cover change.

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