DRIVING FORCE ANALYSIS OF LAND USE AND LAND COVER CHANGE IN BEIJING-TIANJIN ECONOMIC CIRCLE OF CHINA

Wenbo Xu [1], Jinlong Fan [2]

1. University of Electronic Science and Technology of China, School of Resources and Environment, Chengdu, China; xuwenbo@uestc.edu.cn
2. National Satellite Meteorological Centre, Beijing, China; fanjl@cma.gov.cn

ABSTRACT

Research on Land Use and Land Cover (LULC) should date back to five decades ago in the field of geoscience, and the combination of geoscience information system and remote sensing technology has become a mainstream in land use and dynamic monitoring of land cover change (1). In this paper, the research area is Beijing-Tianjin economic circle. Based on the geographic data and 2010 classification data released by Chinese Academy of Sciences, we classify the 1990 and 2000 TM images with object-oriented classification method, and then we analyse the LULC dynamic change spatial-temporally by structure transfer matrixes, the single LULC dynamic degree and the synthesized LULC dynamic degree. At last, based on statistic data, we analyse the driving force of LULC such as economy, population. The results reveal that woodland and grassland has a diminishing tendency from 1990 to 2010; unused land reduces more; wetland has a gradually increasing tendency. There is also a significant reduction in arable land but an obvious increase of artificial surface. Besides, the synthesized LULC dynamic degree is 3.56% and 4.23% in 1990-2000 and 2000-2010, respectively. Moreover, driving force analysis has good consistency with LULC dynamic change results.

INTRODUCTION

Land use usually refers to periodical or long-term activities which human do on the land to satisfy their needs by various means of science and technology (2). Land cover is a new concept with the vigorous development of the remote sensing technology in recent years (3), which usually refers to the sum of all the surface elements, basically contains artificial buildings and natural products, such as buildings, soil, lakes, vegetation, wetland, and so on. With the development of the global environmental change, researches on Land Use and Land Cover (LULC) of changes show its importance increasingly (4).

In this paper, the Beijing-Tianjin economic circle is one of the most rapid developing areas in China, which refers to the large areas of triangle among Beijing, Tianjin and Tangshan. With a total area of $4.2*10^4$ km^2, the region's population is around 29.758 million, which accounts for about 0.4% of the total area and 2.4% of the total population of China, respectively.

In this paper, the data sources include: 1) Basic geographic data: TM/ETM+ images from May to Oct in 1990 and 2000. 2) LULC data: Beijing-Tianjin economic circle 2010

LULC data released by the Chinese Academy of Sciences is used as the classification reference and correct data. 3) Statistic data

METHODS

The work flow of this paper is in Figure 1.

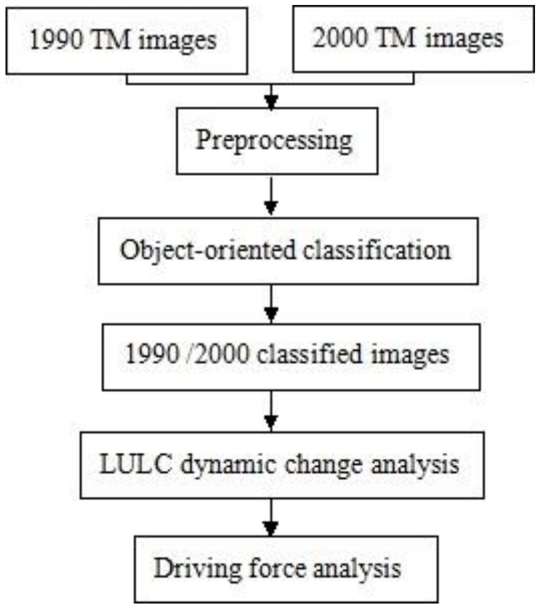

Figure 1: The work flow

Object-oriented classification

Multi-scale segmentation is the basis of object-oriented classification (6). Thus, we try 3 sets of parameters to segment the objects and finally choose the more efficient and reasonable parameter set: segmentation scale 10; shape factor 0.3; compactness 0.5. Then, we classify the 1990 and 2000 TM images by using object-oriented classification algorithm and finally get the results.

LULC dynamic change analysis

Structure changes are analyzed by the area changes and structure transfer matrix (7). And the velocity changes are delineated by the single LULC dynamic degree (8, 9, 10) and the synthesized LULC dynamic degree.

The single LULC dynamic degree delineates the LULC changes of objects in a fixed period of time (11), which is shown by the following formula.

$$L = \frac{U_b - U_a}{U_b} \times \frac{1}{T} \times 100\% \quad (1)$$

Where L is the single dynamic degree, U_a and U_b represents the area of LULC before and after the study time, T is the study time length (12).

The synthesized LULC dynamic degree delineates the ratio of the specific roll-in and roll-out feature type in the study period (13, 14), which is shown as follows.

$$LC = \frac{\sum_{i=1}^{n} \Delta LU_{i-j}}{2\sum_{i=1}^{n} LU_i} \times \frac{1}{T} \times 100\% \quad (2)$$

Where ΔLU_i represents the LULC area of the specific i classes, ΔLU_{i-j} represents the total area of i classes and non-i's type transformation in the study time. T is the study period length.

RESULTS

Classified results

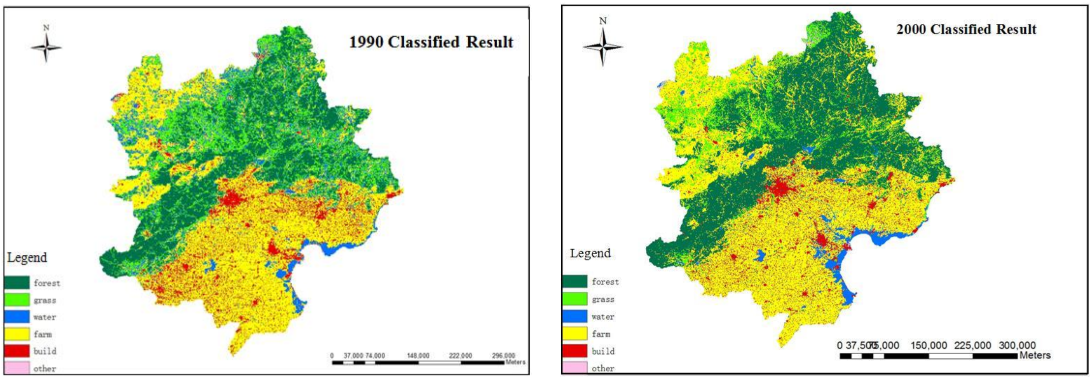

Figure 2: The 1990 and 2000 classified results

Table 1: Statistic and accuracy evaluation of the classified results

Classes	Object-oriented classification			
	Area/ 10^3 km^2		Accuracy	
	1990	2000	1990	2000
Woodland	1.728	1.824	0.7410	0.7726
Grassland	0.395	0.312	0.7901	0.8172
Wetland	0.125	0.130	0.8948	0.9099
Arable land	1.684	1.541	0.8130	0.8377
Artificial surface	0.256	0.369	0.7787	0.8069
Other unused land	0.012	0.024	0.5621	0.5840
Total Area	4.2	4.2	/	
Overall Accuracy	/		0.7856	0.8124
Kappa Coefficient			0.7253	0.7596

We can see that the wetland has the highest extraction accuracy, while the other unused land has the lowest extraction accuracy mainly since that it confuses with other features like low covered woodland and waste artificial surface easily. Both the overall accuracy and Kappa Coefficient of 1990 are lower since the available 1990 TM images' quality is not so good.

LULC Dynamic Change Analysis Results

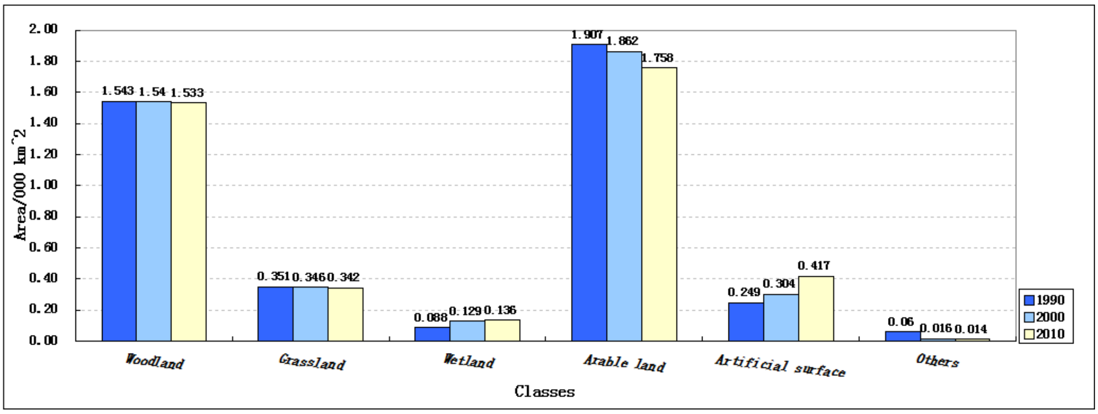

Figure 3: Area changes chart

We can see that woodland and grassland has a diminishing tendency from 1990 to 2010; unused land reduces more; while wetland has a gradually increasing tendency.

Table 2: 1990-2000 Structure transfer matrix (/$10^3 km^2$)

1990	2000					
	Woodland	Grassland	Wetland	Arable land	Artificial surface	Other unused land
Woodland	13256.00	8.40	0.35	19.77	1.26	0.23
Grassland	25.82	3078.00	1.55	19.81	1.87	0.95
Wetland	20.39	28.49	452.00	254.37	75.41	31.34
Arable land	111.62	54.90	61.39	16325.00	218.49	3.60
Artificial surface	31.99	28.23	50.72	434.63	1871.00	4.43
Other unused land	53.90	129.04	74.73	151.88	30.46	135.00

Table 3: 2000-2010 Structure transfer matrix (/$10^3 km^2$)

2000	2010					
	Woodland	Grassland	Wetland	Arable land	Artificial surface	Other unused land
Woodland	12556.00	19.59	0.51	45.94	3.42	0.53
Grassland	21.16	2974.00	0.68	15.79	1.73	0.64
Wetland	3.71	4.41	1182.00	38.97	19.83	3.07
Arable land	240.58	121.54	109.22	16546.00	562.35	6.31
Artificial surface	83.98	70.76	71.98	898.50	1798.00	4.77
Other unused land	2.53	6.14	2.69	6.46	2.17	129.00

Table 4: The single LULC dynamic degree (%)

Index	Classes	1990-2000	2000-2010
L	Woodland	-0.019	-0.045
	Grassland	-0.142	-0.116
	Wetland	4.659	0.543
	Arable land	-0.236	-0.559
	Artificial surface	2.209	3.717
	Other unused land	-7.333	-1.250

As we can see above, the woodland reduces modestly year by year; grassland decreases more and mainly changes into wetland and arable land; wetland increases significantly in 1990-2000 because of the construction of sea ports; arable land and unused land reduces yearly because of the economic driving factors; unused land decreases faster while artificial surface raises lower than the previous decade, which indicates that artificial land is built mainly by reclaiming unused land in the first ten years, while by reclaiming arable land in the last ten years , which further suggests that the per capita arable land decreases, and there is an increase by relying on industrial level development to improve people's living standard.

Driving Force Analysis

Table 5: Driving force information

Driving Force		1990	2000	2010
Economic Elements (billion yuan)	Total Fixed Asset Investment	31.493	233.280	1374.805
	GDP	104.585	643.284	2944.823
Population (million)		340.506	386.36	447.336

Economic elements present positive correlation with the artificial surface, while show negative correlation with arable land and other unused land, which indicates that with the development of economic growth, more and more artificial surface is built at the expense of the cultivated land and unused land.

From 1990 to 2010, the population of the study area increases by 1068.3 million. Thus, a lot of woodland disappears, arable land decreases to satisfy the increasing need of human basic living material.

CONCLUSIONS

Within the scope of the study time, woodland, grassland, and unused land has a diminishing tendency, and arable land reduces significantly, while wetland and artificial surface increases obviously since the development of urban expansion process.

The synthesized LULC dynamic degree is 3.56% and 4.23% in 1990-2000 and 2000-2010, respectively.

Driving force analysis has good consistency with LULC dynamic change results.

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