Land Cover Change Analysis of Hangzhou, China

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Keywords: Land Cover Change, Hangzhou, Landsat Images, Supervised Classification, GIS

Abstract

Hangzhou is one of China's fastest-growing places. Due to the emergence of various e-commerce industries, the number of migrants has increased sharply and the local economy has grown rapidly. These changes have had a large impact on the demand for land utilization in Hangzhou. This study analyzes land cover change in Hangzhou from 2000 to 2018, which provides a reference for the rational planning of land use. Landsat 5 and Landsat 8 images were used for land cover classification, and a land cover change matrix was developed to analyze conversion trends for water bodies, forest, built-up areas, wetlands, cultivated land, and unutilized land. The area percent change and conversion percentage of each class were also determined. A sharp rise in the built-up area, an increase of 199.13%, was discovered after the change detection.

Introduction

Land use and land cover changes have significant spatial-temporal dynamics and can intuitively reflect the impact of human activities on regional land use (Xu, Wang, Zhang, and Yue, 2014). With the acceleration of urbanization, the phenomenon of urban sprawl, which is the inefficient and excessive expansion of urban land use, increased in some large cities in China and has begun to become prominent. At the same time, urban sprawl has brought a series of negative effects, such as environmental pollution, traffic congestion, increases in the input costs of municipal infrastructure, and issues of social inequality (Zhang, Yue, and Fan, 2014). Studying land cover change provides significant guidance for promoting sustainable urban development in order to rationally develop and manage land and maintain a virtuous balance of land ecosystems.

Hangzhou is the capital of Zhejiang Province, which is located on the southeast coast of China. Hangzhou is the political, economic, cultural, educational, transportation, and financial center of Zhejiang Province, and it is also the node city of the Yangtze River Delta Economic Belt. The location of Hangzhou is where rivers, lakes, and mountains blend together. The world's longest artificial canal, the Beijing-Hangzhou Grand, passes through the city, which makes it even more famous. There is an old saying in China: "Up above there is heaven, down below there are Suzhou and Hangzhou." Hangzhou attracts many visitors because of its reputation for unique and magnificent scenery.

In present, whenever Hangzhou is mentioned, people think not only of abundant attractions but also of a company called Alibaba. Alibaba Group is an e-commerce company founded by Ma Yun in 1999. Accompanied by the economic situation and the development of the Internet, e-commerce has brought

Hou, Lu. 2018. Land Cover Change Analysis of Hangzhou, China. Volume 21, Papers in Resource Analysis. 10 pp. Saint Mary's University of Minnesota University Central Services Press. Winona, MN. Retrieved (date) http://www.gis.smumn.edu.

unprecedented opportunities for economic and social development. As the leading new technology industry, Alibaba is slowly transforming the temperament of the city from the bones, so that Hangzhou is also known as the "city of e-commerce." Numerous skilled people from home and abroad have been attracted by Hangzhou (Chen and Zhao, 2017). According to LinkedIn's "China's Workplace Globalization List," published on November 2, 2016, Hangzhou ranked after Shanghai, Beijing, Shenzhen, and Guangzhou. It ranks among the top cities in terms of talent inflows in the new first-tier cities. After the G20 summit was held in Hangzhou in September 2016, the net inflow of population exceeded that of Beijing and Shanghai, and Hangzhou now ranks first in the country (Chen and Zhao, 2017). Thus, the local government began large-scale construction of science and technology parks. However, the development of Hangzhou comes at a cost of reducing arable land and green land.

This study explores land cover change in Hangzhou from 2000 to 2018 using Landsat satellite images and geographic information system methods. The objective of this study is to develop a land cover matrix to conduct a quantitative assessment on land cover change and provide a valuable reference for urban planning.

Study Area

The study area of Hangzhou is shown in Figure 1. The hills and mountains of Hangzhou account for 65.6% of the total area, plains account for 26.4%, and rivers, lakes, and reservoirs account for 8%. It is located at a longitude of 120°09′41″ E and latitude of 30°17′37″ N (Zhejiang Online, 2010). There are eight main districts in Hangzhou city: Yuhang district, Xihu district, Binjiang district, Jianggan district, Xiaoshan district, Gongye district, Shangcheng district, and Xiacheng district. The study area is approximately 3068 km^2 and has a population around 6,896,000. Hangzhou has a subtropical monsoon climate with an average annual temperature of 17.8 °C (Zhejiang Online, 2010).

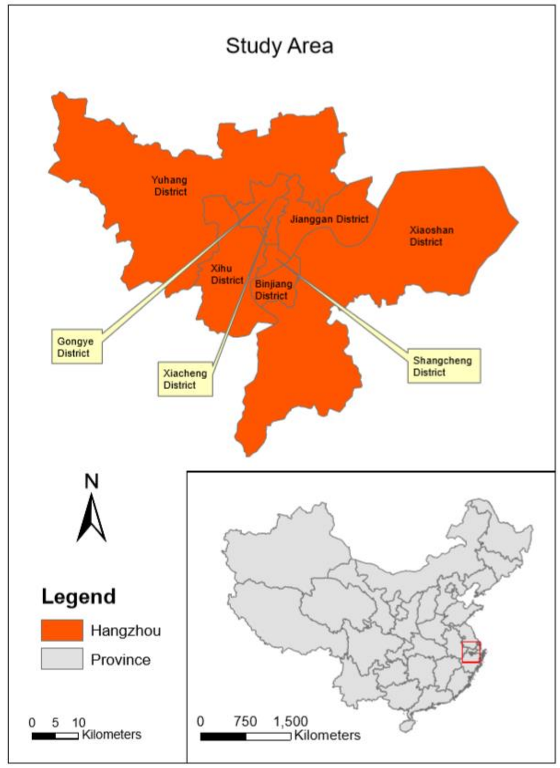

Figure 1. Study area.

Data Processing

The data used in this research are summarized in Table 1. The Landsat 5, Landsat 8 Operational Land Imager (OLI) (path 119 and row 39), and Sentinel-2 images were downloaded from the United States Geological Survey (USGS) EarthExplorer. In order to avoid the impact of the rainy season, the images were selected from May to June, which are dry, and all images were within the same vegetation season. Applying these criteria, the images with better quality were chosen for the study.

Table 1. Remotely sensed data sources.

Acquired Date	Image	Resolution
2000/06/13	Landsat 5	30 m
2018/04/28	Landsat 8 OLI	30 m
2018/04/19	Sentinel-2	10 m

It is a complicated process for remote sensing images to be used as analysis data. Every processing step affects the accuracy of the data, and therefore the results of the analysis. There are two main types of data pre-processing: radiometric correction and geometric correction. Radiometric correction usually includes orthorectification and atmospheric correction. The USGS offers Level 1 and Level 2 remote sensing images. The orthorectification and atmospheric correction has been done by the USGS for Level 1 and Level 2 data. Level 1 data was chosen in this research as Level 2 data started in 2013. According to Song, Woodcock, Seto, Lenny, and Macomber (2001), classification of single-scene remote sensing data using the maximum likelihood method usually does not require atmospheric correction. Thus, the preprocessing of this research focused on geometric correction.

First, referencing the Sentinel-2 image, ENVI software was used to geometrically correct the 2018 TM image and choose 25 ground control points to make sure the RMS error was within one pixel. Then, the corrected 2018 image and the 2000 TM image were used to conduct image to image registration. The RMS error of the re-selected point test was less than 0.5 pixel. In the end, the study area was extracted from the corrected images (He, Shi, Chen and Zhou, 2001).

Methods

Supervised Classification

Based on the primary classification standard from the Chinese Academy of Sciences, there were six land cover types used in this study (Table 2): water bodies, forest, built-up areas, wetlands, cultivated land, and unutilized land. Supervised classification combined with maximum likelihood classification was selected as the approach for image classification (Xu *et al.*, 2014). The training samples were distributed across the entire study area. All seven spectral bands were included in the process and false color was chosen to obtain a better training sample so that the classification results were more accurate. The classification process was conducted in Esri's ArcMap 10.4 software.

Table 2. Land cover classification.

Land Cover Type	Specific Coverage
Water bodies	Lakes, rivers, reservoirs, aquaculture ponds
Forest	Arbor, shrubs, bamboos, coastal mangrove lands
Built-up areas	Urban and rural residential areas, other industrial, mining, transportation sites
Wetland	Natural wetlands, paddy fields
Cultivated land	Dry land, unirrigated paddy fields, vegetable plots, other crop fields
Unutilized land	Barren, grassland, sandy land

Accuracy Assessment

The classification process was straightforward; however, the result can be incorrect if training samples are not well chosen. Accuracy assessment was critical to validate the results of classification. A common way to represent accuracy is in the form of an error matrix.

In this research, random points were generated in ArcMap for both the 2000 and 2018 resulting classification rasters. Then, the point file was converted into a KML file and the KML file was imported into Google Earth. Imagery corresponding to the time periods of this research were selected to get the observed land cover values for the random points (Tuong, Pham, and Lam, 2018). A confusion matrix indicating the concordance of the results of the supervised classification and the observed values was constructed for comparison. There are plenty of measurements to assess the interpretation of the error matrix. Kappa coefficient is one of the most popular measures in addressing the difference between the actual agreement and chance agreement (Tuong *et al.*, 2018). According to Landis and Koch (1977), Kappa coefficients range from 0 to 1. It is considered as a substantial agreement if the Kappa coefficient falls between 0.61 to 0.8, and an almost perfect agreement if the Kappa coefficient falls between 0.81 to 0.99. This study selected substantial agreement as the standard to assess the accuracy of the classification results.

Land Cover Change Matrix

Due to the development of society and the evolution of nature, various land cover types are mutually converted. Therefore, it is not enough to study land cover change only based upon the increase and decrease of the area. In order to further analyze the land type change and internal structure, the land cover transition matrix is often used to describe the changes between various types of land cover. In ArcMap 10.4, the classified images were first vectorized and dissolved, and then used as input to ArcMap's spatial overlay Intersect tool to identify the unchanged and changed areas. Using the Microsoft Excel Pivot Table function, a land cover transition matrix was created, which reflected the amount of conversion between various types of land and the intensity of land changes (Guo and Zhang, 2017).

Land Cover Change Analysis

Area change refers to the change in the extent of a certain type of land cover from the beginning to the end of the study period. Land conversion refers to the conversion of a type of land into other types or other types into the type at the beginning and end of the study period. There are many ways to study land cover change. In addition to common land use dynamics and land use center of gravity transfer model methods employed by Xu *et al.*, 2014; Ma, Huang, and Chen (2018) applied a distinct set of methods to characterize the process and trend of land use and cover change. This study used Ma *et al.*'s methods to analyze the change of Hangzhou land cover. The following equations were implemented in the study:

$$R_s = \frac{U_b - U_a}{U_a} \times 100\%$$

$$= \frac{\Delta U_{in} - \Delta U_{out}}{U_a} \times 100\%$$

U_a= the starting area of type i during the study period
U_b= the end area of type i during the study period
ΔU_{out}= the sum of the area converted to other types
ΔU_{in}= the sum of the area transferred from other types
R_s indicates the single land cover type

area percent change.

$$R_{ss} = \frac{\Delta U_{out} + \Delta U_{in}}{U_a} \times 100\%$$

R_{ss} indicates the conversion percentage of a single land cover type.

$$R_t = \frac{\sum_{i=1}^{n} |U_{bi} - U_{ai}|}{2\sum_{i=1}^{n} U_{ai}}$$

$$= \frac{\sum_{i=1}^{n} |U_{in-i} - U_{out-i}|}{2\sum_{i=1}^{n} U_{ai}} \times 100\%$$

U_{ai}= the starting area of type i during the study period
U_{bi}= the end area of type i during the study period
ΔU_{out-i}= the sum of the area of type i converted to other types
ΔU_{in-i}= the sum of the area transferred from other types to type i
n = number of land cover types
R_t indicates the area change of all types in the study area during the study period.

$$R_{ts} = \frac{\sum_{i=1}^{n} |\Delta U_{in-i} + \Delta U_{out-i}|}{2\sum_{i=1}^{n} U_{ai}} \times 100\%$$

$$= \frac{\sum_{i=1}^{n} |\Delta U_{out-i}|}{\sum_{i=1}^{n} U_{ai}} \times 100\%$$

$$= \frac{\sum_{i=1}^{n} |\Delta U_{in-i}|}{\sum_{i=1}^{n} U_{ai}} \times 100\%$$

R_{ts} indicates the conversion percentage of all types in the study area during the study period.

Luo, Zhou, and Chen (2017) developed an index P_t to reflect the state and trends of land cover change.

$$P_t = \frac{R_t}{R_{ts}} \quad (0 \leq P_t \leq 1)$$

As P_t increases from 0 to 1, it indicates that the land cover type changed from a balanced bidirectional conversion to a one-way unbalanced transition. The index P_t is used to evaluate land cover change.

- When $0 \leq P_t \leq 0.25$, it is a balanced state.
- When $0.25 \leq P_t \leq 0.5$, it is a quasi-balance state.
- When $0.5 \leq P_t \leq 0.75$, it is an unbalanced state.
- When $0.75 \leq P_t \leq 1$, it is an extreme imbalance.

Results

Classification Result

The 2000 and 2018 land cover classification results for Hangzhou are shown in Figure 2 and Figure 3. Table 3 is the error matrix for the 2000 land cover classification, and Table 4 is the error matrix for the 2018 land cover classification.

Land Cover Change Matrix Result

The 2000 to 2018 land cover change conversion matrix for Hangzhou is shown in Table 5.

Land Cover Change Results

Table 6 summarizes both area percent change and the conversion percentage of each land cover type. Table 7 summarizes both area percent change and conversion percentage of all land cover types.

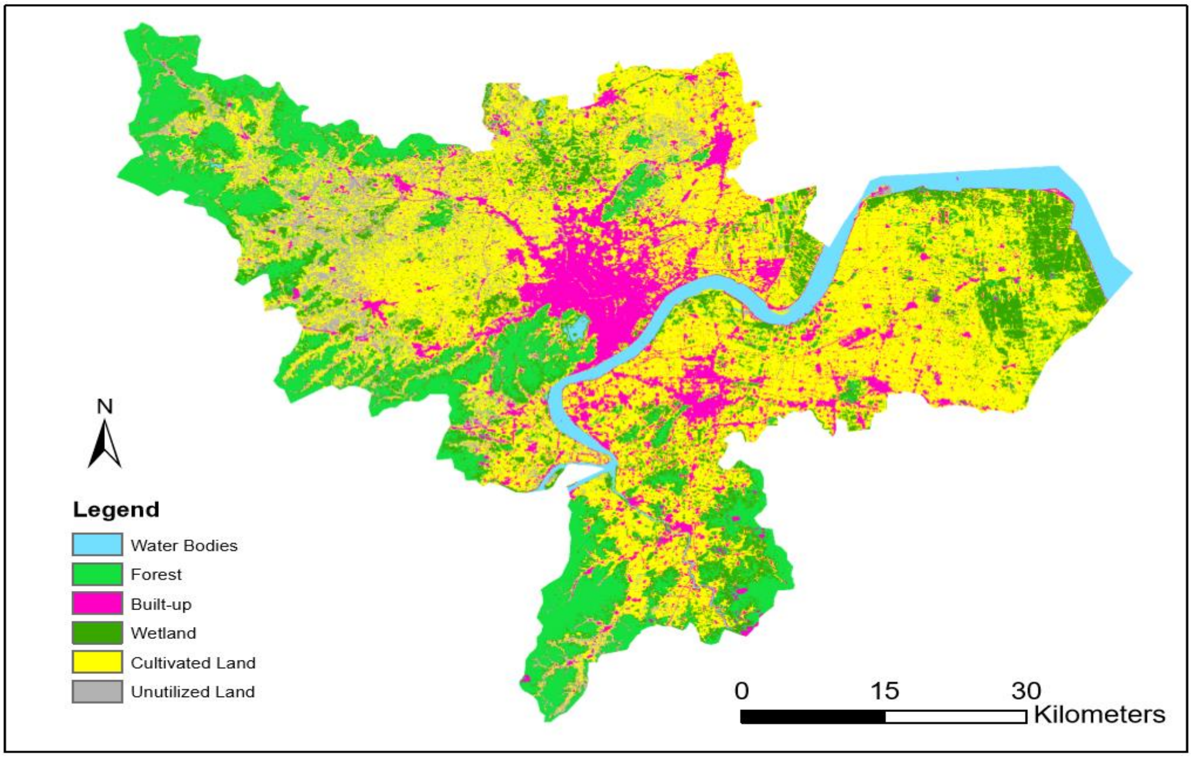

Figure 2. The classification result for Hangzhou for the year 2000.

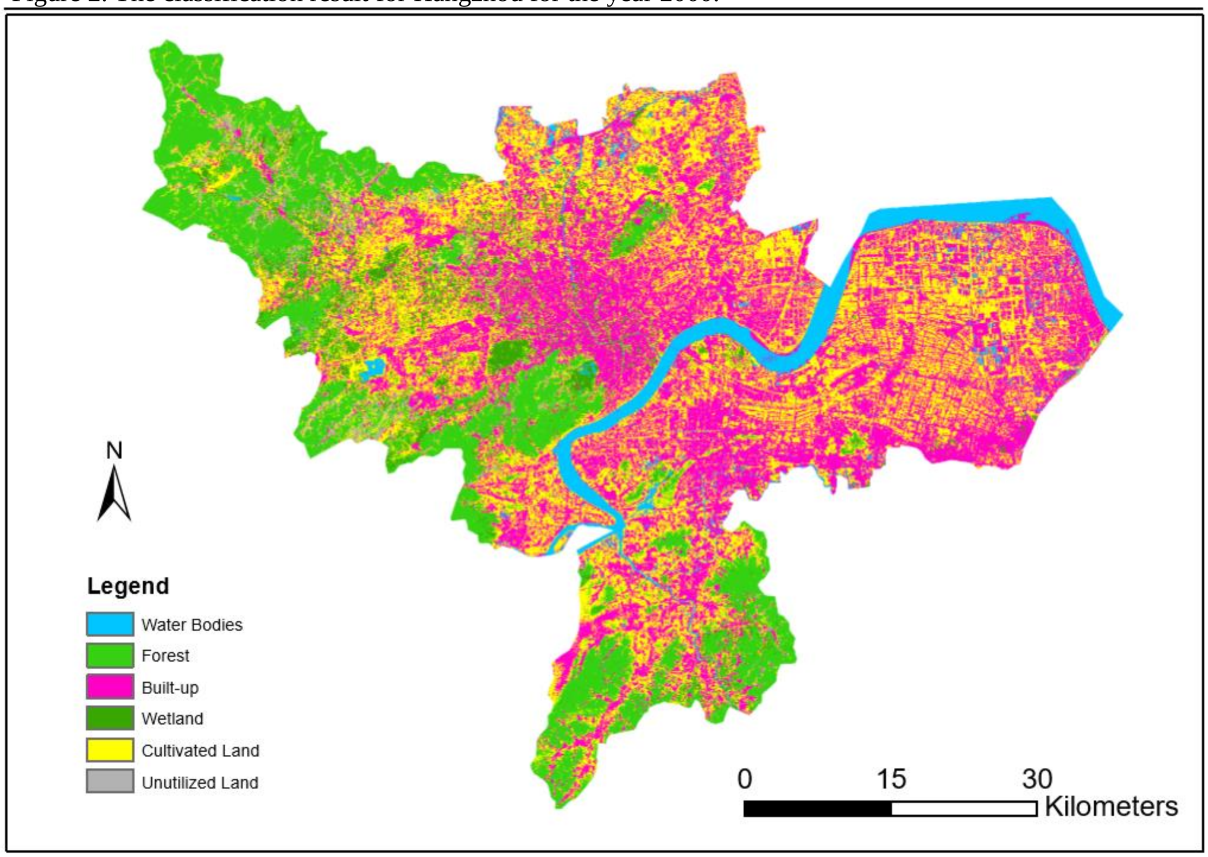

Figure 3. The classification result for Hangzhou for the year 2018.

Table 3. The confusion matrix for the 2000 Hangzhou land cover classification.

Classification	**Google Earth Point**						
	Water bodies	**Forest**	**Built-up**	**Wetland**	**Cultivated land**	**Unutilized land**	**Total**
Water bodies	6	0	1	0	0	0	7
Forest	0	9	0	0	0	0	9
Built-up	1	0	37	0	3	0	41
Wetland	0	2	1	5	1	0	9
Cultivated land	1	3	6	0	39	0	49
Unutilized land	1	0	0	0	2	2	5
Total	9	14	45	5	45	2	120
Overall accuracy	81.67%						
Kappa coefficient	73.88%						

Table 4. The confusion matrix for the 2018 Hangzhou land cover classification.

Classification	**Google Earth Point**						
	Water bodies	**Forest**	**Built-up**	**Wetland**	**Cultivated land**	**Unutilized land**	**Total**
Water bodies	6	0	1	0	0	0	7
Forest	0	4	0	0	0	0	4
Built-up	0	0	55	1	3	0	59
Wetland	1	3	0	4	1	1	10
Cultivated land	0	2	3	0	24	3	32
Unutilized land	0	0	0	0	0	8	8
Total	7	9	59	5	28	12	120
Overall accuracy	84.17%						
Kappa coefficient	76.72%						

Table 5. Land cover change conversion matrix in Hangzhou from 2000 to 2018 (km^2).

	Land Cover 2018							
	Classification	**Water bodies**	**Forest**	**Built-up**	**Wetland**	**Cultivated land**	**Unutilized land**	**Total**
Land Cover 2000	**Water bodies**	132.13	0.39	17.86	3.69	6.42	0.05	160.53
	Forest	1.70	393.74	38.31	25.87	77.63	12.77	550.02
	Built-up	9.74	6.27	285.59	16.27	92.28	3.88	414.03
	Wetland	20.58	90.94	130.78	37.28	147.12	8.84	435.54
	Cultivated land	29.39	43.26	690.39	78.27	670.90	25.55	1537.77
	Unutilized land	5.13	28.71	75.57	29.41	99.65	13.71	252.18
	Total	198.67	563.32	1238.49	190.79	1094.00	64.78	3350.06

Table 6. The area percent change and the conversion percentage of single land cover types in Hangzhou.

Classification	Rs (%)	Rss (%)
Water bodies	23.76	59.14
Forest	2.42	59.25
Built-up	199.13	261.17
Wetland	-56.19	126.69
Cultivated land	-28.86	83.89
Unutilized land	-74.31	114.81

Table 7. The area percent change and the conversion percentage of all land cover types in Hangzhou.

Year	Rt (%)	Rts (%)
2000-2018	26.15	54.23
P_t	0.48	

Discussion

As a result of the continuous urbanization process, the change in the distribution of land cover types shows different characteristics. In general, observations in Figures 2 and 3, the built-up area exhibited a significant upward trend. The areas of cultivated land, wetland, and unutilized land decreased, the water body area increased slightly, and the forest area fluctuation was small between 2000 and 2018 in Hangzhou.

The water body area increased from 160.53 km^2 to 198.67 km^2 as detailed in Table 5. This represents a percent change of 23.76%, and the conversion percentage was 59.14% (Table 6). The main source of water transformation was cultivated land and wetlands. The main shift of water bodies was to construction land. Comparing the water cover in each period, the water body area changed little because the local government tried to protect the natural water bodies. The deviation between years is likely due to the inaccuracy of the interpretation of remote sensing images.

The forest area changed from 550.02 km^2 to 563.32 km^2, which was not a relatively large change (Table 5). The area percent change was 2.42% while the conversion percentage was 59.25% (Table 6). This indicated that the conversion of forest between other types is frequent. The main source was cultivated land and wetlands, and forest transitioned to cultivated land more than to other types. The wetlands in this study contained paddy fields. According to Xu *et al.* (2014), due to the early over-exploitation of mines and low hills, the government actively recommended the policy of returning farmland to forests from 1999 to 2004, which contributed to the overall small change in forest area.

The built-up area increased from 414.03 km^2 to 1238.49 km^2, which was the largest contribution to overall land cover change (Table 5). The area percent change was 199.13% and the conversion percentage was 261.17% (Table 6). The main source of the significant increase in construction land was cultivated land. For the development of local science, technology, and economy, a large number of new industrial parks and residential areas have emerged. Hangzhou rapidly expanded from the central city to the peripheral sub-centers, and the urbanization process is obvious.

The wetland area decreased from 435.54 km^2 to 190.79 km^2 (Table 5). The area percent change was 56.19% while the conversion percentage was 126.69% (Table 6). The majority of wetlands transitioned to cultivated land and built-up areas. The reason for the reduction of wetland areas was the pollution of pesticides and fertilizers. Also, the lack of understanding of the biological value of wetlands led people to convert them to cultivated land (Jin and Liu, 2006).

The cultivated land area decreased from 1537.77 km^2 to 1094 km^2 (Table 5).

The area percent change was 28.86% while the conversion percentage was 83.89% (Table 6). A large amount of cultivated land was converted into built-up land, and the current cultivated land was severely fragmented. Because of the urban expansion, complex traffic lines cut the cultivated land from large contiguous tracts into smaller pieces, and this trend continued to increase.

The unutilized land area decreased from 252.18 km^2 to 64.78 km^2 (Table 5). The area percent change was 74.31% while the conversion percentage was 114.81% (Table 6). The main source of unutilized land was cultivated land. To meet urban development needs, part of the cultivated land was used for urban green land construction. Most of the unutilized land was transformed into cultivated land and construction land. With the spread of the city, the cost of living increased. Some people began to migrate to the outer suburbs; they built houses and developed the barren land into cultivated land.

It can be seen from Table 7 that R_t was 26.15% while R_{ts} was 54.23%, which meant that overall land conversion was much higher than the net area change of all types. The state and trend composite index of land cover change in Hangzhou was 0.48, showing a two-way transformation trend, which is a state of quasi-balanced development. This is conducive to maintaining the balance between all kinds of land cover types.

A limitation existing in this research was the accuracy level of the image classification. The overall accuracy of the year 2000 classification was 81.67% and the kappa coefficient was 73.88% (Table 3). The overall accuracy of the 2018 classification was 84.17% and the kappa coefficient was 76.72%. Both results indicated that the accuracy was sufficient to do the land cover change analysis; however, the accuracy assessment was based on random points. Thus, the result may be different if different points were used. The accuracy assessment could be improved in the future, such as by choosing more points and evenly distributed points manually rather than using the Create Random Points tool.

Conclusions

This paper analyzed the land cover change of Hangzhou from 2000 to 2018 by using remote sensing data and ArcGIS, ENVI, and Excel software. As a result of image classification, six different categories of Hangzhou's land cover were identified: water bodies, forest, built-up area, wetlands, cultivated land, and unutilized land. With the assistance of the land cover change matrix, the land cover conversion directions were discussed as well as the factors that led to the conversion. Also, land cover area percent change and conversion percentage were calculated. The index 0.48 indicated that Hangzhou was experiencing a two-way transformation trend under a state of quasi-balanced development. The major contribution to change was the built-up area, which had a 199.13% area increase and 261.17% conversion due to urbanization. This study may help improve the targeted and effective decision-making of local governments to achieve the goal of sustainable use of land resources.

Acknowledgements

I would like to thank Greta Poser for her patient instructions all the time and especially help with the preprocessing part of this research. Also, I would like to show my appreciation to John Ebert and my friends for their support throughout my studies.

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