

Research and Driving Force Analysis of Remote Sensing Images based on ENVI in Urban Expansion in Xining Municipal District

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ABSTRACT

With the deepening of reform and opening up and rapid economic development, the development of Xining City has been accelerating, and the urbanization level of the study area represented by the municipal district of Xining City has received more and more attention under this social background. Combined with the Landsat remote sensing images from 2008 to 2018 and ENVI processing software, the building information of Xining City was extracted by the methods of Normalized Building Index (NDBI), Improved Normalized Bare Index (MNDBI) and Urban Land Use Index (ULI), and the differences between the three were analyzed by confusion matrix and Kappa coefficient, and the results showed that the total accuracy of NDBI was 78.75%, The Kappa coefficient was 0.56, the total accuracy of MNDBI was 82.50%, the Kappa coefficient was 0.56, the total accuracy of ULI was 92.50%, and the Kappa coefficient was 0.81. On this basis, the results show that the development rate of Xining City was stable from 2008 to 2014, and the development rate increased suddenly from 2014 to 2018, and then the driving factors of the change of construction area were analyzed.

KEYWORDS

Urban Sprawl; ULI; NDBI; MNDBI; Driving Forces; Xining City.

1. INTRODUCTION

Urban expansion refers to the process of continuous expansion of residential and productive land in cities due to the growth of urban population. With the increasing population of China and the gradual acceleration of urban expansion, more and more wasteland around the city is being developed for the construction of residential areas, commercial areas, roads and railways, so that most residents only care about the future construction planning of the city, whether their own land involves demolition and occupation, etc., and the specific changes of urban land in the past are relatively shallow. However, for the overall planning of the city, the changes in urban land use in the past few years can accurately reflect the impact of various factors on the urban area, and analyze and understand the driving forces of urban expansion. Therefore, how to count the changes in urban area and effectively analyze and demonstrate them is also a difficult problem in urban planning. In this study, we will use ENVI software, combined with remote sensing images, and select NDBI, MNDBI, ULI data models to analyze the change trend of urban building land area in the past ten years, and briefly analyze it in combination with the actual situation, and explore the various impacts of policies, transportation and other aspects on urban architecture and economy.

2. SOURCES OF INFORMATION ON THE GENERAL SITUATION OF THE STUDY AREA

2.1. Overview of the Study Area

Xining City is located in the northeast of Qinghai Province, the northeast of the Qinghai-Tibet Plateau, in Huangshui and the confluence of three tributaries, the city is roughly oblique in the shape of a cross. The geographical coordinates are 101°77'E longitude and 36°62'N latitude. Xining City has jurisdiction over the east of the city, the middle of the city, the west of the city, the north of the city four districts, the end of 2012 the central urban area of the built-up area is 150 square kilometers, the urban area of 2261 meters above sea level, belongs to the continental plateau semi-arid climate, the average annual temperature of 7.6 °C. After nearly 50 years of construction, especially since the reform and opening up, Xining's economic development has entered a new stage, and the urban area has been expanding, especially in the south of the city, Haihu New Area and north of the city.

2.2. Sources

In this paper, the Landsat OLI/ETM remote sensing image data downloaded from the geospatial data cloud is selected, the imaging time is 2008~2018, and the resolution is mostly 30 m (the Pan band of Landsat 8 is 15 m). In addition, there are the boundaries of the four urban districts of Xining, as well as Google Maps as a supplementary reference, and the relevant statistics of Xining City.

3. COMPARISON AND SELECTION OF BUILDING INFORMATION EXTRACTION METHODS

3.1. Remote Sensing Image Preprocessing

(1) Radiometric calibration and atmospheric correction

In order to eliminate the error of the sensor itself, determine the accurate radiation value at the sensor inlet, and eliminate the errors caused by atmospheric scattering, absorption, and reflection, ENVI 5.1 software was used for radiation calibration and atmospheric correction.

(2) Cropping of remote sensing images

Since the width of Landsat satellite image imaging is 185 × 185 km much larger than the study area of this experiment, ArcGIS is used to extract the boundaries of Xining municipal districts in "China District and County Boundaries", and then ENVI is used to crop the remote sensing images to obtain the study area.

3.2. Construct the Band Index

There are many methods for extracting building information from remote sensing images, and three methods are selected for comparison.

(1) Normalized Difference Vegetation Index, NDVI

NDVI is used to monitor the growth status of vegetation, vegetation coverage, etc., which can reflect the background influence of plant canopy, and its value is between [-1,1], negative value indicates high reflection area of visible light, such as water, snow, etc., positive value indicates vegetation cover, and increases with the increase of coverage, and zero value indicates rock or bare land. In this study, NDVI is used as part of the other relationships to determine the floor area, which is expressed as the sum of the difference between the reflection value in the near-infrared band and the reflection value in the red band, i.e.:

$$NDVI = (Nir - R) / (Nir + R)$$

(2) Normalized Difference Build-up Index, NBDI

The index method proposed by Zha Yong is indeed an effective method for extracting urban information, which is improved on the basis of predecessors and imitates NDVI, so it is also called the normalized vegetation index, which is fast, effective and highly automated, and has a wide range of applications [1][2] refers to the principle that there is a higher reflectivity in the mid-infrared band (SWIR1) and lower than the reflectance in the near-infrared band (NIR).

$$NBDI = (MIR - NIR) / (MIR + NIR)$$

(3) Modified Normalized Difference Barren Index, MNDBI

There are many improvements to NBDI, and the enhanced building index proposed by Wu Zhijie is also an option, modeled on MNDWI [3], using MNDBI, because NBDI mainly reflects urban and bare land information [1], considering that NDVI reflects vegetation information, then (1-NDVI) reflects non-vegetation information. So adding the two together can give more prominence to the residential information, ie

$$MNDBI = NBDI + (1 - NDVI)$$

(4) Urban land index, ULI

By using the spectral characteristics of vegetation not only but also the spectral characteristics of urban land, the low-density vegetation cover areas extracted by NBDI (the results also include bare land and low-density vegetation cover areas) can be separated from them. The intersection operation is carried out on the basis of NBDI and NDVI normalization. namely

$$ULI = NBDI \& NDVI$$

Landsat 7.			Landsat 8.		
Band Name	Bandwidth (μm)	Resolution (m)	Band Name	Bandwidth (μm)	Resolution (m)
			Band 1 Coastal	0.43 – 0.45	30
Band 1 Blue	0.45 – 0.52	30	Band 2 Blue	0.45 – 0.51	30
Band 2 Green	0.52 – 0.60	30	Band 3 Green	0.53 – 0.59	30
Band 3 Red	0.63 – 0.69	30	Band 4 Red	0.64 – 0.67	30
Band 4 NIR	0.77 – 0.90	30	Band 5 NIR	0.85 – 0.88	30
Band 5 SWIR 1	1.55 – 1.75	30	Band 6 SWIR 1	1.57 – 1.65	30
Band 7 SWIR 2	2.09 – 2.35	30	Band 7 SWIR 2	2.11 – 2.29	30
Band 8 Pan	0.52 – 0.90	15	Band 8 Pan	0.50 – 0.68	15
			Band 9 Cirrus	1.36 – 1.38	30
Band 6 TIR	10.40 – 12.50	30/60	Band 10 TIRS 1	10.6 – 11.19	100
			Band 11 TIRS 2	11.5 – 12.51	100

Figure 1. Landsat 7/8 band comparison

(5) Specific calculation formulas

As shown in Figure 1 and Table 1, when using ENVI and Band Math to extract the normalized vegetation index, a text file and method composed of the Interactive Data Language (IDL) edited by Guo et al. were used [6].

Table 1. The specific formula for the band index

	Landsat 7 ETM	Landsat 8 WAS
NDVI	$(\text{Band4}-\text{Band3})/(\text{Band4}+\text{Band3})$	$(\text{Band5}-\text{Band4})/(\text{Band5}+\text{Band4})$
NDBI	$(\text{Band5}-\text{Band4})/(\text{Band5}+\text{Band4})$	$(\text{Band6}-\text{Band5})/(\text{Band6}+\text{Band5})$
MNDBI	$\text{NDBI}+(1-\text{NDVI})$	$\text{NDBI}+(1-\text{NDVI})$
ULI	NDBI and NDVI	NDBI and NDVI

3.3. Image Binarization to Extract Building Information

Taking the remote sensing image of Landsat 8 OLI on March 22, 2018 as an example, this experiment uses ENVI software to extract the building information by three methods (as shown in Figure 2, Figure 3, Figure 4), and performs binary processing, and the experimental results are as follows (after excluding the surrounding mountains). Comparing the three methods for extracting urban building information, it is found that although the NDBI method is fast and effective, the extraction results include low-density vegetation and bare land information. The extraction results of MNDBI were improved, and the information of urban land use was more prominent, and the information of medium and low density vegetation and bare land was reduced. ULI removes the low-density vegetation information, and the accuracy of the results is further improved, which is a better extraction method.

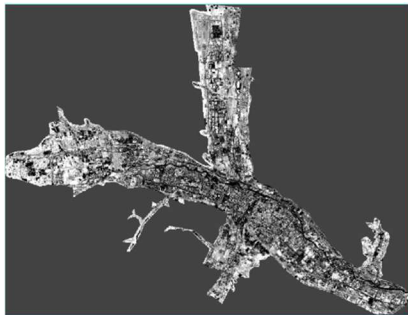


Figure 2. 2018 NDBI

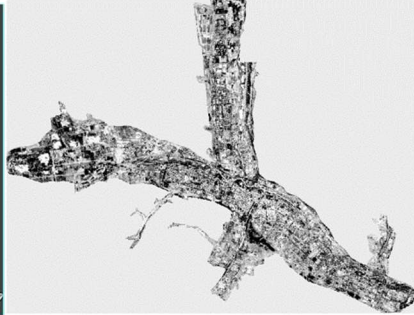


Figure 3. 2018 MNDBI

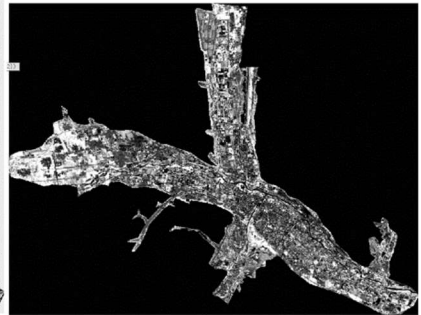


Figure 4. 2018 ULI

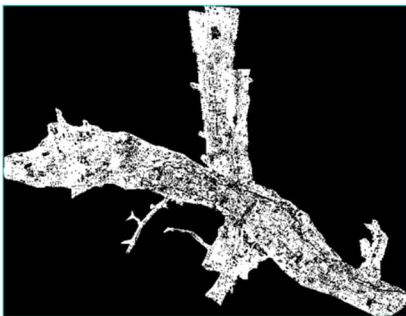


Figure 5. 2018 NDBI
binarisation results

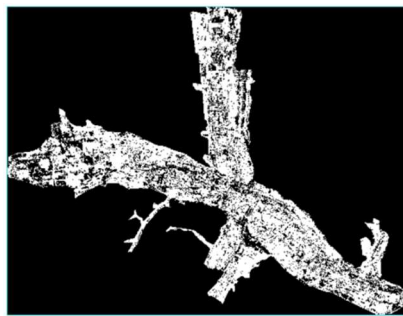


Figure 6. 2018 MNDBI
binarisation results



Figure 7. 2018 ULI
binarisation results

3.4. Confusion Matrix Accuracy Evaluation

In this experiment, high-precision scale images (Landsat 8 Pan band with 15 m resolution) and related data (Google Maps) were used as the comparison materials for verification (without any processing)

[4], and 80 verification points were randomly generated in the study area using ArcGIS for human-computer interaction verification. The results calculated using the confusion matrix [3] (Table 2, Table 3, Table 4) show that the accuracy of the extraction using the Urban Land Use Index (ULI) is higher.

Table 2. NDBI accuracy verification data

NDBI	Land for construction /km ²	Non-building land /km ²	Total number of cells	User accuracy /%
Land for construction	41	13	54	75.93
Non-building land	4	22	26	84.62
Producer precision	91.11	62.86	80	
Total accuracy	78.75%	Kappa=0.56		

Table 3. MNDBI accuracy verification data

MNDBI	Land for construction /km ²	Non-building land /km ²	Total number of cells	User accuracy /%
Land for construction	51	10	61	83.61
Non-building land	4	15	19	78.95
Producer precision	92.73	60.00	80	
Total accuracy	82.50%	Kappa=0.56		

Table 4. ULI accuracy verification data

ULI	Land for construction /km ²	Non-building land /km ²	Total number of cells	User accuracy /%
Land for construction	56	4	60	93.33
Non-building land	2	18	20	90.00
Producer precision	96.55	81.82	80	
Total accuracy	92.50%	Kappa=0.81		

Kappa analysis is a multivariate statistical method used to evaluate classification accuracy, where the Kappa coefficient refers to the proportion of the evaluated classification that decreases in error compared to random classification:

where K denotes the Kappa coefficient; a_{ij} denotes the element in column i , row j ; r

denotes the number of rows of the error matrix; $\sum_i$ denotes the sum of line i ; $\sum_j$ denotes the sum of column j ; N represents the total number of samples [5].

In summary, the accuracy of the ULI method is good, with a total accuracy of 92.5% and a Kappa coefficient of 0.81, so the ULI method is selected for the extraction of building information in the subsequent processing.

4. CHANGES IN THE AREA OF THE FOUR DISTRICTS UNDER THE JURISDICTION OF XINING CITY

4.1. ULI Extraction Results and Urban Building Analysis

Using ENVI software, the original bands were used to construct the NDVI and NDBI index bands, and then the ULI bands were constructed and the extracted ULI results were binary to analyze the construction area of Xining City, and the three-year processed images were taken as an example for comparative analysis, Figure 8, Figure 9 and Figure 10 were the binary extraction results of ULI in 2008, 2014 and 2018 respectively, and the comparison showed that the building density of Xining Municipal District increased significantly.

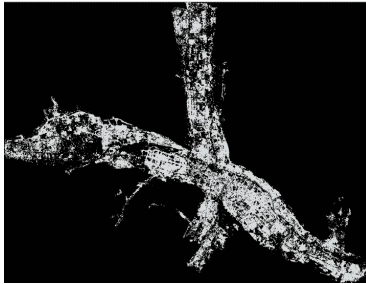


Figure 8. 2008



Figure 9. 2014

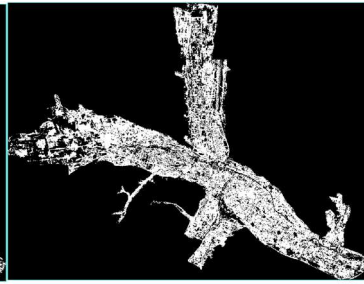


Figure 10. 2018

4.2. Analysis of the Area of Municipal Districts

In the ENVI software, the construction area of the municipal district in 2008~2018 was obtained by statistically counting the number of pixels of each processed photo, and the statistical analysis was carried out with Excel, and Figure 8 was obtained, and the results were divided into two periods, namely 2008~2014 and 2014~2018.

4.3. Result Analysis

As can be seen from Table 4, the floor area of the municipal district in 2018 was 1.58 times that of 2008. In 2008~2014, the average annual growth rate of the construction area was 2.77, and the average annual expansion of the construction area of the municipal district in 2014~2018 was 6.52, which shows that the area of the municipal district of Xining City has developed rapidly in recent years, and the area expansion rate is gradually improving.

5. DRIVING FORCE ANALYSIS

(1) National policies and government initiatives will be combined. At the beginning of the century, the Xining Municipal Government actively pursued economic development, establishing Dongchuan Industrial Park and Bio Park in the east and north of the city respectively, driving the economic development and urban construction of the vicinity. In 2006, taking the express train of the "Eleventh Five-Year Plan for the Development of the Western Region", the industry developed rapidly and accelerated the construction of the city. In 2008, Nanchuan Industrial Park was added, and the characteristic industries were further developed and the economic level was steadily improved.

(2) Transportation development and inflow of tourists. The opening of the Qinghai-Tibet Railway in the strategy of large-scale development of the western region has brought a wide range of qualified personnel and investment to Xining City, and its economic level has begun to develop. In 2011,

Xining Railway Station began to expand and open high-speed rail EMU trains, and a large number of tourists flowed into Xining, further developing the tourism economy.

(3) Population dispersion and the establishment of commercial districts. The establishment of Haihu New Area and Chengnan New Area has dispersed the population pressure in the city center, and also injected economic vitality into the east of the city and the total village in the city.

6. CONCLUSION

The results of this study show that the construction area of the four districts of Xining City is increasing year by year, and the main reason is that while the economy of Xining City is developing rapidly, it needs to meet the needs of housing for all kinds of population, and the construction area of commercial use is increasing year by year, and the economic development is closely related to national policies and provincial initiatives. It is precisely because of the country's emphasis on the northwest cities, the introduction of all kinds of talents by the Qinghai Provincial Government, and the joint efforts of migrant workers and local residents that Xining has become a plateau pearl of economic development, people's happiness and national unity in the past ten years.

ACKNOWLEDGEMENTS

Funding: This work was supported from the projects of "The Natural Science Basic Research Plan in Shaanxi Province of China (Program No. 2024JC-YBQN-0329). Internal scientific research projects of Shaanxi Land Engineering Construction Group (DJNY2023-TD-1, DJNY-ZD-2023-3, DJNY2024-16, DJNY2024-36).

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