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Study on Land Use Classification of Weinan Based on Landsat8

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Abstract: Rapid and accurate monitoring of the dynamic change of construction land is of great significance for strictly controlling the arbitrary growth of urban construction land and protecting agricultural and forestry land. In order to master the situation of land use change and conduct more efficient research on urban land use classification, this paper takes Weinan as the research object and uses Landsat8 data under the same classification conditions to analyze the image features of various land use types respectively by using minimum distance, maximum likelihood and random forest method, and carries out land use classification research. The research shows that for the selected research area, the maximum likelihood classification method has higher classification accuracy and time efficiency, while the minimum distance and random forest can not reflect its superior classification performance, and the overall accuracy is lower than the maximum likelihood classification method, and the maximum likelihood classification method has obvious advantages. Therefore, in the classification of remote sensing image, the maximum likelihood classification method is suitable when the data dimension is low.

Keywords: Landsat 8, Minimum distance, Maximum likelihood method, Random forest.

1. Introduction

With the development of social economy, the contradiction between population, resources and environment becomes increasingly prominent[1]. As an indispensable part of the development of human society, land resources' utilization and changes have an important impact on the development of human society and economy[2-3]. The economic development and the increase of population have forced the expansion of human activities, the continuous expansion of building area, and the tension between man and land. The change of land use/cover has caused a significant impact on the ecological environment[4]. At the present stage, the contradiction between man and land has seriously affected the sustainable development of social economy. Timely mastering of land utilization is the basis for rational management of land resources[5]. Since its development, remote sensing technology has shown its macro, dynamic and real-time characteristics, playing an important role in vegetation cover research, land use change, and crop monitoring in the commercial field. The classification and processing of land use information and vegetation distribution information by using remote sensing technology will bring more economic benefits and far-reaching influence to the future urban and rural land planning of the country. Therefore, the research on land use and land cover change has become the forefront and hot field of global environmental change research[6].

2. Overview of the Study Area

Weinan, a city belonging to Shaanxi Province, is located between 108°50 '-110°38' E and 34°13 '-35°52' N. It is located in the east of Weihe Plain in Guanzhong, Shaanxi Province. The terrain takes Weihe River as the axis, forming five major geomorphic types, namely, two mountains in the north and two tableland in the south and Pingchuan in the middle. The terrain belongs to the Shaanxi-Gansu-Ningxia basin margin area of the North China Platform. The geology presents a ladder graben structure with north-south uplift and central fault depression. North and south high, middle low, open east and west, was upturned tile. It is 330 to 2,645 meters above sea level. The periphery is tableland, cultivation has a long history. The southern loess tableland is interspersed with flood fans and the northern and southern margins are stony mountains.

3. Data Sources and Research Methods

3.1. Data Sources

Landsat8 satellite is the latest data support system for Earth observation in the United States, which was successfully launched in 2013. It continues to provide continuous observation data for the global ecological environment instead of Landsat7 satellite, inherits the tradition of previous series, and provides multi-band, medium-high resolution images[7]. Landsat 8 provides multi-spectral 8 bands with a spatial resolution of 30 m and a panchromatic band with a spatial resolution of 15m, in addition to thermal infrared data.

Data in this paper are from the website of the United States Geological Survey (USGS). Landsat 8 images are used as the data source, and images in 2020 are selected for analysis. In order to better classify land use types in the study area, images from June to September when vegetation growth was in good condition were selected. The time of image data collection was close, which greatly reduced the difference in classification results caused by the difference in spectral information. In order to better identify ground object information, false color synthesis was carried out on 2020 TM image respectively, using the synthesis method of 5, 4 and 3 bands. After that, initial processing such as geometric correction and image Mosaic was carried out to obtain the TM false color composite image in the study area, as shown in

Figure 1.

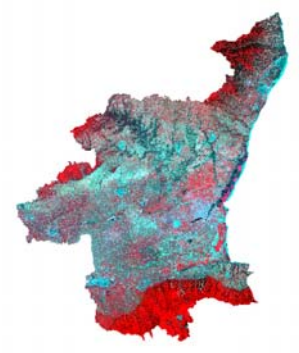


Figure 1. False-color image of band 5, 4 , 3 in the synthesis study area

3.2. Determination of land types and selection of samples

The problem of land use is complicated. The change of cultivated land and construction land area is a typical representation of urban urbanization and industrialization. The less cultivated land is, the more construction land is, which indicates the higher degree of urbanization and industrialization. On the contrary, the more cultivated land, the less construction land, indicating the lower degree of urbanization and industrialization. The change of the area of woodland, grassland and water area can represent the ecological environment of a region. The more obvious the reduction of the area of grassland, woodland and water area, it indicates that the ecological environment of the region has been seriously damaged. At the same time, the selection of training samples should also consider the main land use types and research purposes in Changchun. Therefore, the training sample types in the study area are classified into five categories: construction land, cultivated land, grassland, forest land and water body. Land for construction refers to land for building buildings and structures, including land for urban and rural housing and public facilities, land for industry and mining, land for energy, transportation, water conservancy, communication and other infrastructure. Arable land is land used for direct production of crops. The land mainly growing herbs and shrubs is classified as grassland, and the land mainly growing trees is classified as woodland. Water areas mainly include rivers, lakes, reservoirs, pits and ditches.

In order to facilitate the selection of various training samples and precision verification samples, the standard false color band combination is used to display remote sensing images. Based on the visual analysis of the images, this paper defines the classification categories of the images as water body, grassland, cultivated land, forest land and construction land in a self-defined form. Then, according to the relevant contents of remote sensing image interpretation, interpretation marks of each land type are established, as shown in Table 1.

Table 1. Signs of feature interpretation

classes	image feature	Typical image
construction land	Cyan, cyan gray, gray, uneven tone, geometric shape features, clear boundary	
grassland	Light red, more blurred, irregular shape, flaky	
woodland	Dark or dark red, linear distribution	
cultivated land	Red, regular shape, concentrated distribution	
water	Grey, grey black, white or yellow-green, regular shape, straight distribution	

3.3. Research Methods

Spectral image classification can be divided into supervised classification and unsupervised classification[8]. Supervised classification, also known as training classification, simply refers to the process of using the sample pixels of the confirmed category to identify the pixels of other unknown categories. The key lies in the selection of training samples and training sites, and the quality of the selection is related to whether the classification can achieve good results[9]. According to the selected samples, the ground object identification. In this study, the minimum distance method, maximum likelihood method and random forest method of supervised classification method were used to classify the land use of Weinan City. By comparing the classification accuracy of the three classifiers, the method more suitable for the land use classification of Weinan City was selected.

Minimum Distance method is the Euclidean distance between the pixel to be divided and the mean vector of the

training sample as the classification scale. By calculating the Euclidean distance between all the pixels to be divided in the whole image and various centers, the Euclidean distance from the pixels to be divided into the same category is the smallest[10].

Maximum Likelihood method is the most widely used supervised classification method based on Bayes classification criterion, assuming that the probability distribution of each category is normal, and then the category of each pixel is specified according to the assumption of the similarity of spectral properties and the maximum probability of belonging to a certain category[11].

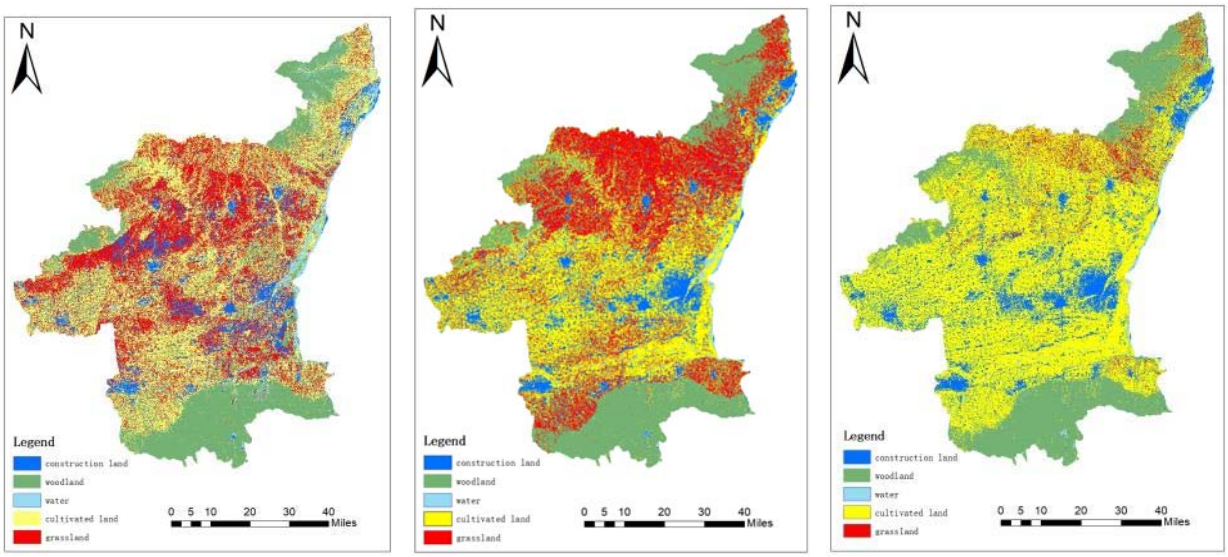
Random Forests is an integrated learning algorithm based on CATR decision tree proposed by Breiman of the American Academy of Sciences. Random forest is a non-parametric pattern recognition classification method, which can be applied to most data classification instead of knowing or assuming the distribution of data in advance, which is also the key to superior to traditional statistical learning methods [12].

4. Classification Results and Analysis

In this paper, Landsat 8 remote sensing images were used to test the classification results of different classifiers. According to the selected samples, three classifiers, minimum distance, maximum likelihood and random forest, were used to classify the land use types of the images in the study area, and the accuracy verification samples were used for verification.

4.1. Classification Results

The classification results of the three methods of minimum distance, maximum likelihood and random forest were compared and analyzed, as shown in Figure 2. The results show that the three classifiers are consistent in the classification of woodland land and construction land, and can identify well. For cultivated land and grassland, due to their similar spectral characteristics, the three classifiers are not very ideal for the classification of cultivated land and grassland. The random forest has the largest confusion for cultivated land and grassland, the minimum distance misclassifies cultivated land into grassland more, and the maximum likelihood method has less error and error. For water body classification, the results of the three classifiers are basically the same, but the water boundary of random forest classification is not clear compared with the other two classifiers. Therefore, according to the classification result map, maximum likelihood method is more suitable for land use classification in the selected research area.



(a)Minimum Distance (b)Maximum Likelihood (c)Random Forests

Figure 2. Classification result

4.2. Accuracy evaluation

The purpose of classification accuracy evaluation is to analyze the results after classification by using statistical methods. At present, the most commonly used Confusion Matrix proposed by Congalton is used to calculate Product Accuracy, User's Accuracy and Overall accuracy Accuracy) and Kappa coefficient. The value range of Kappa coefficient is [-1,1]. In practical application, the value of Kappa coefficient is generally between [0,1]. The value of Kappa coefficient is [0.21,0.4], indicating that the classification results are generally consistent. [0.41,0.6] indicates that the classification results have moderate consistency; [0.61,0.8] indicates high consistency of classification results. [0.81, 1.00] indicates high consistency and almost complete consistency. The accuracy assessment of classification results is shown in Table 2.

Table 2. Precision evaluation table of land use classification results in the study area

Method	accuracy	Woodland (%)	Grassland (%)	cultivated land (%)	construction land (%)	Water (%)
Minimum Distance	Product Accuracy	90.62	56.88	39.70	78.53	78.22
	User's Accuracy	78.41	20.18	73.97	78.40	53.07
	Overall Accuracy (%)	72.34		Kappa		0.6728
Maximum Likelihood	Product Accuracy	94.18	85.68	76.54	94.56	82.90
	User's Accuracy	93.34	67.94	89.35	91.72	74.09
	Overall Accuracy (%)	85.2804		Kappa		0.8206
Random Forests	Product Accuracy	91.6	35.8	49.96	80.58	76.45
	User's Accuracy	90.52	29.74	62.3	74.32	66.1
	Overall Accuracy (%)	67.758		Kappa		0.5609

According to the classification result comparison and accuracy evaluation of each classifier, the results show that: The overall classification accuracy of minimum distance method, maximum likelihood method and random forest method was 72.34%, 85.28% and 67.758%, respectively. The results showed that maximum likelihood method had the highest classification accuracy for land use in Weinan City, and the Kappa coefficients of the three classifiers were 0.6728, 0.8206 and 0.5609, respectively. From the perspective of Kappa coefficient, the classification of maximum likelihood method is highly consistent with the actual ground objects, and the classification results are ideal. The overall results show that for the Landsat8 remote sensing images selected in this paper, the classification accuracy of maximum likelihood is the highest and the classification effect is the best, indicating that when Landsat8 images with fewer features are used for classification, the faster maximum likelihood classification method can be used.

5. Conclusion

In this paper, different classifiers were used to classify the land use in the selected study area, and a more suitable land use classification method was selected through comparison. The results showed that: The maximum likelihood method has an ideal land use classification effect and speed in Weinan, and the classification results are highly consistent with the distribution range of real land features, so it is more suitable to be applied to urban land use classification. However, this study also has some limitations. Whether the conclusions can be applied to more seasons and regions needs further research. In addition, different selection of classifiers and different study areas also have a certain impact on the classification results of Landsat8 remote sensing image data. The above deficiencies need to be further studied in the next stage.

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References

[1] Liu Xiaojing, Feng Zheng. Analysis of land use change in Changchun City Based on Landsat TM image [J]. Digital Technology and Application, 2018(10):3.

[2] WANG L X. Analysis of land use change in suburban Harbin City based on TM Remote sensing image. Agricultural Mechanization Research, 2007(9):3.

[3] Pei Tong, Shan Yongjie. Analysis of Land use Change in Urban areas Based on Landsat TM Remote Sensing image [J]. Technology and Industry, 2002,22(10):400-404. (in Chinese)

[4] Wang Zhaoli, Zeng Lechun. Research progress on the impact of regional land use change on ecological environment in China [J]. Graduate Journal of Sun Yat-sen University: Natural Science & Medicine, 2005, 26(3):10.

[5] SHAO K. Research on land cover change detection based on high resolution remote sensing images. Huazhong University of Science and Technology, 2014.

[6] Shao Meiyun, Wang Lu. Analysis of urban land use change in Beijing. Gansu Science and Technology, 2013, 29(18):3. (in Chinese)

[7] Land use classification of Hefei based on Landsat8 remote sensing image [J]. Hubei Agricultural Sciences, 2015, 54(15):6.

[8] Liao Dong, Dai Hongbao, Xu Jiying. Comparison of Land use classification Methods based on Landsat-8 Supervised Classification and unsupervised Classification [J]. Henan Science and Technology, 2019, 000(008):14-16.

[9] Sun Wenrui, Jiang Huifang, Zuo Xiaoqing, et al. Comparative analysis of multiple classifiers for Landsat8 image classification [J]. Geospatial Information, 2022(020-001).

[10] Xiao Fan, Guo Junjun, Zhang Mengjie. Research on Land use Classification Based on Landsat8 data and Supervised classification method [J]. Anhui Agricultural Science Bulletin, 2020, 26(8):4.

[11] Zhou Lihong, Wu Hao. Classification analysis of land use in Nanchang County based on landsat8 Remote sensing image [J]. People's Yangtze River, 2017(S2):4.

[12] Li Qing, Shi Minwei. Research on Land use Classification of Multi-temporal Landsat8 based on Random Forest [J]. Information Technology and Informatization, 2019(7):3.