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Land Use Classification Study based on Landsat 8 OLI Time Series Imagery and Support Vector Machine

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Abstract: Accurate classification of land use types is of great significance for urban planning and effective utilization of land resources, and although remote sensing data have been successfully used in land use type classification studies, previous studies were mostly based on single-period remote sensing imagery, ignoring the phenological characteristics on vegetation time series. Therefore, in this study, based on Landsat 8 OLI remote sensing images for the whole year of 2017, land use classification research was carried out on different time series (single-period, growing season, non-growing season, and annual data) imagery data through the support vector machine algorithm, respectively, with a view to exploring the influence of time series on land use classification, and thus improving the classification accuracy.

Keywords: Landsat 8 OLI; Time Series; Remote Sensing; Land Use Type Classification.

1. Introduction

Land use type reflects the way human beings utilize the land cover types on the earth's surface, and it is classified into different land use types according to the differences in land use in different regions [1,2]. Classification study on the current land use status is an important work to grasp the current status of surface resource utilization and formulate reasonable land planning policies to realize the rational utilization of surface cover resources [3-5]. Accurate classification of land use types helps to understand the land use situation of a feature in a certain time period, so as to carry out effective planning and utilization of resources.

With the rapid development of remote sensing satellite technology, computer technology and other technologies, obtaining land use information based on remote sensing data has become an important means in the field of land resource management [6-8]. However, previous studies on land use classification based on remote sensing were mostly based on single-period remote sensing image data, ignoring the climatic characteristics of vegetation in the process of time change [9].

In this study, based on the Landsat 8 OLI remote sensing images for the whole year of 2017, the land use classification study was carried out by processing and parameter extraction of the image data and utilizing the support vector machine algorithm on the image data of different time series (single-period, growing season, non-growing season, and annual data) respectively, with a view to exploring the influence of time series information on land use classification, and then realizing the land use type and then realize the high-precision classification of land use types.

2. Study Area and Data Presentation

2.1. Overview of the Study Area

The study area is located in Jingyuetan District, Changchun City, Jilin Province (E125°21′, N43°52′) in northeastern China, which contains Jingyuetan National Forest Park, which preserves a relatively complete vegetation ecosystem, and at the same time is located in the suburbs of rapidly expanding cities, so the study area has complex surface cover types, mainly including woodland, residential land, water, grassland, cropland, and unutilized land. There are mainly forest land, residential land, water area, grassland, cultivated land and unutilized land.

2.2. Landsat OLI Data

In order to study the effect of time series on the results of land use type classification, Landsat 8 OLI image data of 2017, i.e., January 12th, April 2nd, June 5th, August 24th, September 25th, November 12th and December 14th, 2017, which contain less clouds in the study area, were selected in this study, respectively. Meanwhile, in order to study the effect of growing and non-growing seasons of vegetation on the results of land use type classification, the image data of seven months were categorized into growing (November, December, January, and April) and non-growing (June, August, and September) seasons based on the phenological characteristics of vegetation in the study area.

3. Data Processing and Research Methodology

3.1. Landsat OLI Data Processing

The downloaded Landsat OLI data are upper atmospheric reflectance data, which will be affected by the atmosphere for the land use type classification study. In order to eliminate the effect of the atmosphere and further improve the classification accuracy, the upper atmospheric reflectance data should be converted to surface reflectance data, so this study will perform radiometric calibration, atmospheric correction, image cropping and other processing on the downloaded Landsat OLI data to obtain the image data of the study area. Therefore, in this study, the downloaded Landsat OLI data will be radiometrically calibrated, atmospherically corrected, and image cropped to obtain the image data of the study area.

3.2. Parameter Extraction

Vegetation index can effectively characterize different vegetation cover conditions on the ground surface, and thus it is widely used in land use, vegetation classification and environmental change studies. Based on this, this study extracted the band information and four commonly used vegetation indices, such as Normalized Difference Vegetation Index (NDVI), Ratio Vegetation Index (RVI), Difference Vegetation Index (DVI) and Normalized Difference Vegetation Index (NDVI). Vegetation Index (DVI), and Enhanced Vegetation Index (EVI), detailed descriptions of each vegetation index are given in references [10].

3.3. Classification Methods

Support vector machine is a new type of computer algorithm based on statistical theory, the constraints of its optimization is to take the training error as a reference, to achieve the minimum error as the goal of training optimization, and its ability to identify different features is significantly better than some traditional learning methods [14]. Support vector machine has a more obvious advantage in solving a small study area, it basically does not involve complex probability and data operations, and the theoretical structure is simple, not subject to the limitation of the number of training samples, and thus can well solve the problem of small number of samples and so on. In summary, the support vector machine has the advantages of high accuracy of classification results in small areas and high computational efficiency. Therefore, in this study, the support vector machine algorithm is chosen to classify different time series image data.

4. Results and Analysis

4.1. Classification Results based on Single-Period Image Data

The results of land use classification based on single-period remote sensing image data are shown in Table 1, from which it can be seen that the land use classification results based on June remote sensing data have the highest accuracy, with an overall accuracy of 93.77% and a Kappa coefficient of 0.92; followed by the classification results based on September remote sensing data, with an overall accuracy of 92.09% and a Kappa coefficient of 0.89; and the classification results based on December remote sensing data have the lowest accuracy, with only 78.81% and a Kappa coefficient of 0.71. data had the lowest classification accuracy of 78.81% with a Kappa coefficient of 0.71.

Table 1. Classification results based on single-period image data

Month/Month	1	4	6	8	9	11	12
Overall Accuracy	84.74%	87.45%	93.77%	89.47%	92.09%	90.96%	78.81%
Kappa coefficient	0.80	0.83	0.92	0.86	0.89	0.88	0.71

The classification results based on the remote sensing data in June are shown in Figure 1, it can be seen that the classification results based on the remote sensing images in June, forest land, residential land, water and cultivated land have high classification accuracy, and the production and user accuracy are higher than 90%, while the classification results of the unutilized land and grassland are poorer, in which the grassland has the poorest classification results, and the production accuracy is only 43.75%, and the user accuracy is 28.00%. The classification results of grassland are the worst, with production accuracy of 43.75% and user accuracy of 28.00%.

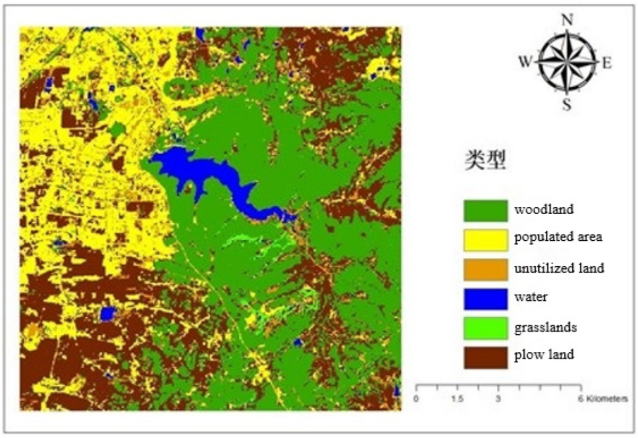

Fig 1. Land use classification map based on June image data

4.2. Classification Results based on Vegetation Growing Season Image Data

The results of land use classification based on the growing season remote sensing image are shown in Figure 2. It can be seen the accuracy of land use classification based on the growing season remote sensing image is relatively high, which is 94.64%, and the Kappa coefficient is 0.93, in which the classification accuracies of forest land, residential land, water area and arable land are all higher, whereas the accuracy of the classification of grassland is lower, with the production accuracy of only 43.75% and the user accuracy of only 35.00%. is also only 35.00%.

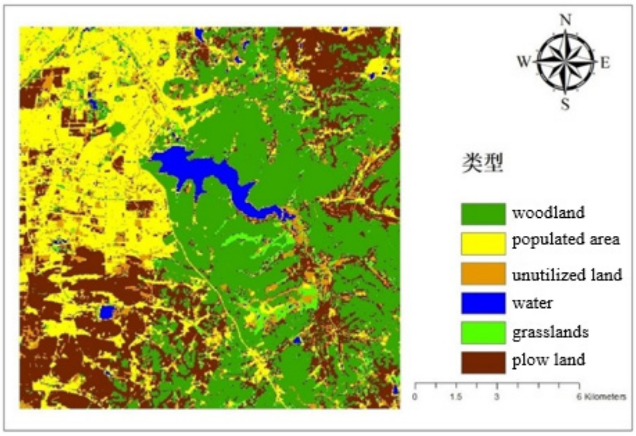

Fig 2. Land use classification map based on vegetation growing season image data

5. Conclusion and Discussion

This paper carries out a land use type classification study based on time series Landsat 8 OLI image data, and carries out a comparative study based on the classification results of single-period and time series remote sensing image data respectively, to explore the influence of time series information of remote sensing data on the classification results of land use type, and the conclusions obtained are mainly as follows:

Among all the single-period remote sensing image data in 2017, the classification result based on June remote sensing data has the highest accuracy, with an overall classification accuracy of 93.77% and a Kappa coefficient of 0.92, which indicates that the remote sensing data at the beginning of the vegetation growing season is the most suitable for land-use type classification research.

The results of this study show that the introduction of time series information can improve the accuracy of land use classification results, but the classification accuracy of unutilized land and grassland in all classification results of annual time series image data is relatively low, only about 60%, and there is still a large room for improvement, so in the future research, we can try to longer time series image data, such as the use of remote sensing image data of 2 years or longer time series to improve the accuracy of land use classification results. Therefore, in the future research, we can try to use longer time series image data, such as using two years or longer time series remote sensing data for land use type classification research to improve the accuracy of land use type classification results.

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