ISSN: 1813-4890

Research Progress on Fine Classification of Crops

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Abstract

The investigation of crop planting structure plays a very important role in the development of fine modern agriculture. In recent years, with the gradual improvement of the availability of medium and high-resolution remote sensing data, the research on crop classification using remote sensing technology is becoming more and more extensive. This paper summarizes the relevant research done by some scholars in recent 5 years from four aspects: data type, classification method and accuracy, and the advantages and disadvantages of different methods.

Keywords

Data type, classification method, classification method.

1. Introduction

Traditional land use classification uses single optical remote sensing data as the main data source, and in many cases, the classification accuracy is not ideal. Compared with land use type, crop classification has higher data requirements. The results of crop classification based on middle and low resolution optical remote sensing data are obviously less accurate. Traditional vegetation index time series methods based on Modis, Landsat, HJ and AVHRR are not applicable in the southern region where crop planting structure is complex. In recent years, more and more researchers have used multi-source remote sensing data combined with machine learning and deep learning to extract crop classification and achieved good classification results. However, for crop classification, there are great differences in data availability, crop planting type and plot size between regions, and it is very difficult to explore universal methods applicable to different regions. At present, few studies have proposed a classification method that applies to all regions. Based on this, this paper aims to make a comparative analysis of the relevant research paradigms in recent years, trying to explore better data acquisition and classification methods from the regional scale..

2. Theoretical basis of fine classification of crops

The difference of spectral characteristics of crops is the most important theoretical basis for fine classification of crops. For different crop types, their reflectance spectral characteristics are the most important characteristic information of remote sensing images. The different colors of different crops in different band combinations are the main basis for their classification. Secondly, the periodicity of its growth process is an important sign that distinguishes it from other green vegetation. At different growth stages, the components of crops are constantly changing, resulting in differences in spectral characteristics, vegetation index, leaf morphology and water content, which is also one of the theoretical bases for distinguishing different crop types. In addition, objective cognitive experience and statistical data also have very important reference value for crop classification. For example, in the southern region, rice, peanut, soybean and other crops are the main crops, and the regional differences are large, the fragmentation degree of land is higher, and the resulting spatial heterogeneity is also stronger. In the northern region, wheat, corn and sorghum are the main crops, and most crops are distributed in a contiguous manner, with little regional difference and low spatial heterogeneity. Based on this, we need to take the above three features as the theoretical basis of classification, that is, spectral features, time features and space features. Fully explore the differences in spectrum, phenology and texture between different crops and between crops and other ground object types..

3. Regional differences in crop classification studies

From the process of literature review, it can be seen that the research results on the fine classification of crops in the northern region are much more than those in the southern region, which is caused by many reasons. First of all, from the perspective of the difficulty of data acquisition, the days in which high-resolution remote sensing data can be obtained in the northern region account for 40%-50% of the days in the whole year, while the days in the southern region only account for about 10%. Secondly, from the perspective of planting structure, the crop planting structure in northern China is relatively uniform, with large planting plots, obvious boundaries between plots, and low spatial heterogeneity. Finally, from the perspective of crop planting types, crop types in the northern region are relatively simple, and fewer types need to be considered in crop classification. For the southern region, due to the great differences in terrain and climate factors, there are great differences in crop planting types among provinces. Even for a small area, the planting types of adjacent plots are different. It adds difficulty to the fine classification work. How to increase the depth and breadth of related research in the southern region while deeply studying the rationality of planting structure in the northern region is a key issue that needs to be considered at present.

4. Moving from a single data source to multiple data sources

Data selection is the basic premise of crop classification. The traditional crop classification is mainly based on single optical data, supplemented by statistical data to investigate the planting structure. However, due to the low resolution of some optical images, there are some problems such as fuzzy boundary and large scale error in classification, so the accuracy of classification results is often not ideal. For example, Wang Chencheng et al. [1] used SAR data to extract corn, soybean and rice in Nong 'an County, Jilin Province, and the overall accuracy was 66.67%. Liu Jie et al. [2] used Landsat8 data to classify and extract rice, corn, cotton, winter wheat and various fruit trees in Wensu County, Xinjiang, and found that the classification accuracy of corn and pear trees was very low, which was 53.9% and 66% respectively. It shows that single data source still has great limitations in crop extraction. With the increasing requirement of classification accuracy in modern agriculture, the classification accuracy obtained by a single remote sensing image cannot meet the application requirements. In recent years, the increasing number of high-resolution remote sensing satellites has greatly promoted the application of remote sensing technology in crop fine classification. More and more scholars have begun to classify ground objects by combining multi-source remote sensing data, and found that compared with a single data source, the classification accuracy has increased by 5%-10% under other equal conditions. For example, Zhang Ying et al. [3] combined Sentinel-1 SAR data and Sentinel-2 optical data to extract wheat, cotton, rice and garlic in the southwest of Jining, and the classification accuracy reached 89.62%, while the classification accuracy was only 72.78% when only optical Sentinel-2 was used for extraction. The extraction accuracy of SAR data is 69.28%. Ruiyuan Li et al. [4] extracted the planting area of rice (early rice and late rice) and wheat in southeast Anhui province by combining Modis data and Landsat data, and made full use of the temporal resolution of Modis data and the spatial resolution of Landsat, with the overall classification accuracy up to 90.0%. It shows that multi-source data fusion is of great significance to improve crop classification accuracy. Combining optical data, radar data, statistical data and other multi-source data to extract crop planting spatial structure features will also become one of the mainstream trends of crop classification in the future [10].

5. Application and development of different classification methods in crop classification

The selection of classification method is the most critical factor in crop extraction. A suitable classifier can greatly improve the classification accuracy of crops. Methods based on traditional supervised classification and unsupervised classification are not widely used in crop extraction. As the methods of maximum likelihood and minimum distance in ENVI only rely on prior knowledge and spectral characteristics of ground objects to distinguish, for crops, there will be a large number of phenomena of "different spectrum of the same object" or "foreign body in the same spectrum" in the classification, which reduces the accuracy of classification results. With the deepening of research and application of machine learning model and deep learning in remote sensing field. In crop fine classification, object-oriented classification, random forest classification and other machine learning methods have been recognized and accepted by most relevant scholars. For example, Tao Li et al. [5] extracted crop information in the hilly areas of the middle and lower reaches of the Yangtze River by using random forest classification method, and the overall accuracy and Kappa coefficient obtained were 96.3% and 0.954, respectively. By taking spectral features, texture features and shape features as nodes of decision tree, different weights are set for different features. Through parameter adjustment, high precision classification results are obtained. When Du Baojia et al. [6] extracted the crop planting structure in Bei 'an City, Heilongjiang Province, an object-oriented classification method was adopted to obtain plots of different sizes by scale segmentation of different crop types, and each plot was taken as a classification object to reduce spatial heterogeneity during classification. Li Qianjin et al. [7] used the object-oriented and convolutional neural network model to identify crops in South Dakota, a transition zone between the grasslands and the Rocky Mountains in the Midwest of the United States. By segmentation, the land of different sizes was taken as an object, and the red-edge band of the wide-format camera Gaofen-6 was introduced for classification, achieving ideal classification results. The biggest advantage of object-oriented classification in crop extraction is its scale difference. Since crop planting is based on the scale of plots, there may be heterogeneity among different plots. In particular, there is the problem of mixed pixels at the boundary of the block. Compared with the traditional object based on pixel scale, the spatial heterogeneity and boundary ambiguity can be better solved by object classification oriented to the block scale. The key of random forest classification lies in the selection of characteristic factors, and the selection and weight distribution of factors have a key impact on the final classification result. The Convolutional neural network model is also widely used in crop classification, which is to screen the input characteristic variables through multi-layer neural network and extract the most appropriate classification factors. In general, the advantages of machine learning models and neural networks in crop classification make their application in different regions constantly improve. However, the superiority of classification method still needs the support of appropriate data and characteristic variables.

6. Effects of taxonomic characteristics on fine classification of crops

The key of feature classification is feature extraction. The classification based on single feature to multi-feature is one of the main trends of remote sensing classification. For crops, classification based on single feature mainly uses the time difference characteristics of crop growth, obtains the difference points of crop growth through NDVI or EVI curve, and extracts different crop types according to expert knowledge or empirical method. For example, Ping Yuepeng et al. [8] used MOD09Q1 from June 2012 to June 2014 and MOD09A1 from April to May 2013 in Songnen Plain as data sources, and used TIMESAT software for smoothing noise reduction processing to construct NDVI time series curves and extract seven crop phenological characteristics. The overall classification accuracy is 76.47%. Shi Xian et al. [9] used Sentinel-2 images to extract the planting structure of winter wheat in Jiaozhou City according to the rules shown by EVI curves of winter wheat, potato and peanut. Because winter wheat has an obvious bimodal pattern during its growth, and its growth period is different from that of rice, the two can be quickly identified by the curve. Although the method of crop recognition based on a single image is simple and efficient, it makes full use of the temporal change characteristics of crop growth and has obvious advantages in crop recognition, especially in areas with simple planting structure [10]. However, for complex planting areas, single feature extraction has great limitations. Therefore, in the area with many planting types and broken plots, it is necessary to distinguish according to the multi-feature index of crop growth period. Although the comprehensive use of multi-feature crop classification can enrich the information of remote sensing data and improve the classification accuracy to a certain extent. However, excessive feature components will lead to information redundancy, which will affect the classification accuracy [10]. Liu Yi et al. [11] studied the impact of feature selection and convolutional neural network on crop classification accuracy, extracted RVI, GI, NDVI, EVI, GVI, TVI and other index information during plant growth, and screened each feature quantity through ReleifF algorithm. The weight of each feature quantity is determined by its ability to distinguish near samples. The higher the weight, the greater the impact on crop classification. Finally, NDVI, EVI and RVI are selected as the final classification index. It is found that the classification accuracy is obviously improved compared with using all the feature quantities. Ao Weizang et al. [12] extracted different land classes by selecting different feature variables in the study of Gaofen satellite data in non-grain monitoring of permanent basic farmland. When distinguishing between water and non-water bodies, the shape factor weight is set to 0.1 and the smoothness factor is set to 0.5. At the same time, the water body index NDWI is used as the main feature. It is found that water body and non-water body can be well distinguished under this condition. When subdividing non-water bodies, not only spectral features and shape features are added, but also texture features GLCM Mean are added to better distinguish farmland, greenhouse facilities and buildings. It is found that the accuracy of the extracted ground objects is above 80%. Kristof Van Tricht et al. [23] made full use of the advantages of Sentinel-1 data and Sentinel-2 data when classifying crops, and extracted three texture features of crops, homogeneity, heterogeneity and entropy, from Sentinel-1 data. According to Sentinel-2 data, spectral data of four bands were extracted, and normalized vegetation index NDVI was extracted from them. Four crops of cotton, rice, capsicum and maize were extracted by the combination of texture features and spectrum-time series features. Cao Weinan et al. [13] extracted 11 common vegetation indices to describe the amount, growth and coverage of vegetation. At the same time, eight texture parameters, such as mean value, second moment, entropy, contrast and homogeneity, were extracted by gray co-occurrence matrix to characterize crop texture information. Subsequently, OFI function was used to select the best index factor and obtain the crop planting information in Liaoning region. Although multi-feature parameter extraction of crops can improve crop classification accuracy to a certain extent, the increase of feature vectors will not only reduce the data processing speed, but also cause the accumulation of errors. Therefore, how to grasp the quality and quantity of feature factors is a key technology for multi-feature classification [10]. In addition, how to combine spectral features with other features is also a problem that needs to be focused on.

7. Summary and prospect

In recent years, agricultural remote sensing has made great progress both in theory and technology. The fine classification of crops is an important branch of agricultural remote sensing. Its research process plays a very important role in promoting the development of modern agriculture. In the next few years under the background of "non-food", the extraction of crop planting structure will be an important part of agricultural remote sensing. The current research mainly focuses on two aspects: one is to extract crop planting structure or single crop planting information by using spectral features of remote sensing images or temporal vegetation index of remote sensing; The second is to extract large-scale crop planting information based on low resolution remote sensing images or to monitor crop growth in small areas based on high resolution. From the perspective of research paradigm, crop fine classification methods have gradually changed from single data source to multi-source data combination, from traditional supervised classification methods to deep learning and machine learning methods, and from single feature quantity to multi-feature quantity optimization direction. The combination of multi-source data and the application of intelligent methods are the main development trends at present. Although the combination of spatio-temporal multi-scale data plays a great role in promoting regional crop extraction, how to coordinate the temporal, spatial and spectral resolution of data sources is still a key problem that needs to be solved. Secondly, due to the complex terrain conditions in China and the large differences in planting structure between regions, how to extract crop planting structure in a larger area is one of the goals of future classification work.According to the research results of many scholars, the domestic research on crop classification is mainly in the northern region. This is closely related to the fact that the three northeastern provinces are the most important granary in China, and the rationality of their grain planting structure is directly related to China's grain production security. But from another point of view, this is also very much related to the difference in data acquisition conditions and crop planting structure in the northern and southern regions. The southern region has abundant rainfall and water, and also has important food production value. Therefore, increasing the extraction of crop planting structure in the southern region, especially in the cloudy and foggy areas of the middle and lower reaches of the Yangtze River, is still a big technical problem, which requires the joint efforts of relevant researchers.

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