Method for crop classification based on multi-source remote sensing data

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Abstract. Using remote sensing images to classify crops to obtain spatial distribution of different crops is of great significance for crop yield estimation and agricultural policy formulation. Due to the phenomenon of the same spectrum from different materials or the phenomenon of the same materials with different spectrum, it is difficult to obtain accurate crop classification results from single-phase images. We take a farm in Lintong District of Xi'an as the research area. The crops in this study area are mostly cross-planted, and the planting area is small, so it is difficult for the traditional classification method. In order to increase classification accuracy, a multi-level classification method is proposed in this paper. The Sentinel-1 backscattering coefficient (Sigma) of image is used to pre-classify the ground in the study area, and the Sentinel-2 images which cover the crop growth cycle in the study area are used to construct a normalized vegetation index (NDVI) time series to distinguish the growth differences of different crops. Combined with field survey data and phenological characteristics of crops, on the basis of pre-classification, SVM (Support Vector Machine) method is used to classify Sentinel-2 images. The classification accuracy reaches 98.07%, which is much higher than the minimum distance, Mahalanobis distance, neural network, expert decision tree, object-oriented and other classification methods.

1. Introduction
Agriculture is the foundation of our national economy. Using remote sensing technology can not only extract crop information, carry out growth analysis, yield forecasting, pest and disease monitoring, crop quality remote sensing inversion, crop water stress inversion, etc., but also classify crops to adjust agricultural structure and promote resources in agricultural production process reasonable distribution.

At present, the research on crop classification at home and abroad mostly uses optical remote sensing data with spectral information of ground objects. The use of remote sensing technology to identify crops is easy, but the identification and classification of different types of crops is difficult. Due to the variety of crops, different types of crops will show similar characteristics (the phenomenon of the same spectrum from different materials) on remote sensing images; while the same crops will be affected by weather, planting methods and other factors. They will show different spectral characteristics in the image (the phenomenon of the same materials with different spectrum). Therefore, multi-temporal images can be used to extract many crop information and improve classification accuracy. At the same time, Normalized Difference of Vegetation Index (NDVI) can be used to reflect the growth characteristics of crops, and then to differentiate the types of crops. This method has been widely used in the classification of crops, such as: Liu Mingyue [1] et al. combined with multi-temporal Landsat 8 OLI images and object-oriented classification method, with Bei'an City, a key grain-producing area in Heilongjiang Province as the research area, obtained the spatial distribution information of crops in this area; Ma Li [2] et al. used multi-temporal NDVI and crop classification of characteristic bands, the planting information of Heilongjiang Friendship Farm was successfully extracted, and the overall
classification accuracy reached 98.77%. Xu Qingyun [3] et al. based on MODIS NDVI time series data, using Savitzky-Golay filtering method and quantitative comparative analysis successfully identified the types of five crops in Shaanxi Province; Han H [4] et al. extracted the area and types of crops in the black river and obtained better classification results based on multi-temporal NDVI data.

With the development of radar remote sensing technology, radar images have all-weather, all-day ground observation characteristics that are not limited by illumination and weather conditions. Applying it to the field of crop monitoring has also become a research hotspot. For example, studies have shown that the advantages of combining Synthetic Aperture Radar (SAR) imaging with optical imaging to identify and monitor rice are incomparable with traditional monitoring methods [5-6]; Guo Jiao [7] et al. merged the Sentinel-1 and 2 images to classify the crops, and the results showed that the accuracy of classification after fusion is higher than optical classification; Zeyada[8] et al. combined the multi-polarized Radars-2 data with various classification methods to improve the recognition accuracy of crops; Li [9] et al. used the multi-temporal Sentinel-1 data to monitor the corn planting area in Zhuozhou City, Hebei Province, and obtained long-term sequence radar image classification results with higher single-phase classification accuracy and Kappa coefficient. Therefore, combining SAR images with optical images can help improve the recognition accuracy of crops.

The open access of Sentinel data provides a good data foundation for crop classification research. The spatial resolution of radar image data in Sentinel-1 interference mode is 5m×20m. Sentinel-2 optical image has the advantages of high resolution of 10m, 20m and short revisit period. This paper takes a farm which locates in the north of Weihe River in Lintong District, Xi'an City, Shaanxi Province as a study area Pre-classifies it with Sentinel-1 radar image and Google Earth image. Sentinel-2 optical image is used to construct NDVI time series and use the SVM method to classify crops. The results show that the method adopted in this paper has higher classification accuracy and meets the requirements of crop classification.

2. Materials and methods

2.1. Overview of the study area

The study area has shown in figure 1, locates in Lintong District, Xi'an City, Shaanxi Province, is in the eastern part of the Guanzhong Plain. The geographical coordinate of the center is 109°13′04″E and 34°30′17″N, as shown in Figure 1. Study area's climate is typical sub-humid warm temperate continental climate characterized by hot and rainy summers, cold and dry winters with an average annual temperature of 13.4 °C and annual precipitation of 500-800 mm. The main arable crops including wheat, cole, sweet potatoes, cabbage, etc. The summer harvest crops are mainly winter wheat and cole. According to statistics, winter wheat planting area in the region accounts for 55% of the total crop planting area, which plays an important role in food production in the region.

2.2. Data source and pre-processing

Due to the short growth cycle of most vegetable in this area, this experiment is based on the 13 Sentinel-2 images, which are sourced from the European Space Agency's website (https://scihub.copernicus.eu/). The radar image of Sentinel-1 is selected for pre-classification at the same period with Sentinel-2 and using google earth image as a reference for field investigation, which is prepared for assisted classification.

Using the Sen2cor plugin provided by ESA in the SNAP software, the acquired Sentinel-2 L1C data is subjected to radiometric calibration and atmospheric correction. Then the L2A data is produced, showing in Table 1. In addition, ENVI 5.4 software is used to perform geometric correction, atmospheric correction and radiation calibration for the image covering the whole growth cycle of wheat.
2.3. Method
Firstly, the acquired multi-source remote sensing data is preprocessed, and the NDVI time series is constructed by using Sentinel-2 optical images. Then using the pre-classification results of Sentinel-1 backscattering characteristics, we choose six different classification methods (neural network, object-oriented, expert decision tree, minimum distance, Mahalanobis distance, support vector machine) to obtain classification results. Based on the results, SVM is used as classifier to reclassify Sentinel-2. Finally, we performed accuracy evaluation of the proposed method proves that the multi-level classification is precise and robust.

2.3.1. Pre-classification. The radar scattering coefficient, also called the backscattering coefficient, refers to the reflectivity of the radar in the incident direction of the target unit cross-sectional area, which represents the parameter of the scattering intensity in the incident direction. From the scattering characteristics of the Sentinel-1 images, it can be concluded that the image brightness represents the backscattering intensity, and the roughness of the inner surface of the pixel is proportional to the backscattering intensity. Due to the small variety of field spacing in selected test areas, the classification result is susceptible to construction land, roads and houses. Therefore, the backscattering characteristics of the Sentinel-1 radar image are pre-classified, and the influencing factors such as the house and road are removed, which contributes to the improvement of crop classification accuracy.

The pre-classified results are shown in Figure 2. There is a big difference in the trend of the linearized backscattering coefficient of each feature in different time periods. It can be seen that the backscattering coefficient of the water is the lowest and the change trend is relatively slow. Buildings are significantly higher than the vegetation and cultivated land. Because the vegetation in the study area is less than crops,
the backscattering coefficient of vegetation is low and the trend is not obvious. But the cultivated land is higher than that of planting. From March to May, the growth period of crops in this area is strong and the backscattering coefficient of the wheat showed a gradual increase. Then it begins to grind and grout. After June, because the wheat is harvested, the backscattering coefficient gradually decreased.

![Graph showing backscattering characteristics in the study area.](image)

**Figure 2.** Characteristics of backscattering characteristics in the study area.

2.3.2. **Construction of NDVI time series.** The ratio calculation based on the difference in the reflectance of the crop in the near-infrared band and the red band can highlight the characteristics of crops in the image and extract the crop category. Therefore, this experiment mainly uses the Normalized Difference Vegetation Index (NDVI) to extract agricultural information. The formula is [10]:

$$NDVI = \frac{NIR - R}{NIR + R}$$

NIR: Near-infrared reflection value
R: Red band reflection value

It can be seen from Figure 3 that the sowing period of wheat is from October to November, and the seedlings emerge about 1 week after sowing, during this period the NDVI value gradually increases. The first peak of wheat appeared in November. From December to January, wheat hardly stopped growing, and the NDVI curve showed a downward trend. By the end of February, wheat began to turn green, and the NDVI value continued to rise. When the value of the wheat reached the second peak, the other crops in this period have low NDVI values, which can better distinguish wheat from other crops. Finally, the wheat harvested in early June.

The planting time of cole is nearly to the wheat. From early to mid-October, the individual plant of cole is too small to generate the value of peak. Until the first ten-day and midmonth of March of the next year, the growth of cole is still slow, and the NDVI value is also low. Until late March, cole entered
the flowering stage, and began to grow rapidly. By mid-May, the NDVI curve reached its peak in the pod setting stage. After the harvest, the NDVI value of cole decreased significantly.

The sweet potato is planted between late March and early April, and the NDVI curve began to rise. Then the stem and leaf of sweet potato began to grow rapidly, and the NDVI curve continued to rise. By mid-June, the sweet potato is getting bigger, the curve increased significantly. Until the sweet potato is harvested, the peak of NDVI value appears.

As the Figure 4 shown, the planting time of cabbage is roughly from late January to early February, and the cabbage curve rises smoothly. When it enters the rosette period, the NDVI value begins to increase rapidly, which is the highest value.

2.3.3. Classification method. Based on the NDVI time series, the crops are classified. In order to obtain better classification results, when we choose the selection of training samples, it must be ensure that the calculated sample separation should be greater than 1.8. In the test, we use the data obtained by the testers after field investigation as the training samples, which can reduce the possibility of misclassification. The calculated results show that the selection of training samples is reasonable, and the separation between different types is greater than 1.9. Then, using the decision tree, object-oriented, minimum distance, Mahalanobis distance, neural network, support vector machine and other methods to classify the crops, and the accuracy of the results obtained by pre-classification and non-pre-classification are analyzed and compared.

3. Results and Analysis

3.1. Sentinel-2 optical image classification results
In this experiment, firstly the backscattering coefficient of the Sentinel-1 radar data is used to pre-classify for the crops in the study area, then the NDVI time series is constructed and classified by five different methods. The results are shown in Figure 4: (a) object-oriented, (b) neural network, (c) expert decision tree, (d) minimum distance (e) Mahalanobis distance.
Figure 4. Comparison of five classification results.

The Kappa coefficient and classification accuracy of the seven classification methods are shown in Table 1:

| Types                      | Overall accuracy% | Kappa coefficient | Mapping accuracy% | User accuracy% |
|----------------------------|-------------------|-------------------|-------------------|---------------|
|                            |                   |                   | Wheat             | cabbage       | sweet potato  | Cole          |                   |
| Minimum Distance           | 91.25             | 0.88              | 94.52             | 90.37         | 88.25        | 92.36         | 89.93            | 92.36         | 85.27 | 91.38 |
| Mahalanobis Distance       | 92.39             | 0.87              | 94.97             | 91.27         | 89.46        | 93.28         | 95.24            | 90.73         | 86.08 | 92.33 |
| Expert Decision Tree       | 92.58             | 0.89              | 94.39             | 92.21         | 90.03        | 91.92         | 93.31            | 93.05         | 90.15 | 92.28 |
| Object-oriented            | 93.74             | 0.92              | 95.21             | 93.71         | 90.23        | 92.25         | 95.66            | 92.47         | 88.36 | 91.73 |
| Neural Network             | 94.76             | 0.91              | 96.74             | 94.52         | 91.09        | 93.88         | 94.56            | 94.67         | 90.02 | 94.22 |
| Support Vector Machine     | 95.39             | 0.93              | 97.73             | 94.21         | 92.36        | 94.72         | 96.13            | 95.29         | 91.75 | 95.21 |
| Proposed method            | 98.07             | 0.95              | 98.88             | 95.31         | 92.93        | 95.74         | 97.63            | 96.25         | 94.47 | 94.39 |

It can be seen from Table 1 that the seven classification methods have achieved high precision. The overall accuracy is above 90%, indicating that the Sentinel-2 optical image has a good prospect in the classification of crops.

3.2. SVM classification results before and after pre-classification

According to the backscattering characteristics of different features, the backscattering coefficients of different features are extracted. Using ENVI decision tree classification, we set different thresholds according to the backscattering coefficients of different features, and the study area are divided into four categories: cultivated land, vegetation, houses, water, of which cultivated land is the area to be classified.
in the next step. Based on the pre-classification result and Sentinel-2 image NDVI time series, SVM classification is performed in Sentinel-2 image. The classification result is shown in Figure 5 (b):

![Figure 5](image)

(a) SVM.  
(b) Proposed method.

Figure 5. SVM classification results before and after pre-classification.

Compared with other methods, it can be seen from Figure 5 (b) that the accuracy of proposed method is significantly improved. Compared with the common SVM classification, the classification accuracy is further improved by the SVM method after pre-classification, which can be more clearly reflected the spatial distribution of different crops. In addition, those with smaller planting areas such as cole and cabbage, can also achieve higher classification accuracy.

4. Conclusion

This paper uses Sentinel-1 radar image, Sentinel-2 optical image and Google Earth image as the data source to construct the NDVI time series covering the main crop growth cycle of the study area, and proposes a multi-level classification method to classify the main crops in the study area. Research indicates:

1. Using the six classification methods to classify the crops in the study area, the overall accuracy of each method is above 90%. It indicates that using Sentinel-2 optical image to construct the NDVI time series can achieve high precision classification of crops, and the support vector machine method has the highest precision, reaching 96.39%.

2. The multi-level classification method proposed in this paper has obtained a good result in the study area. The overall classification accuracy is 98.07%, which is more accurate than the support vector machine method.

3. This paper uses Sentinel-1 radar image and Sentinel-2 optical image to classify crops and achieve higher classification accuracy. Sentinel satellite is part of ESA's Earth observation plan, its free access characteristic and high resolution makes the Sentinel data have great potential in applications such as crop classification.

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