Extraction of Crop Planting Structure in County Based on Multi-temporal Images of Sentinel-2

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Abstract. Accurate land information using was the foundation of the modern agriculture. The Sentinel-2 images were used as data sources in this paper. Firstly, spectral curve analysis of the features in the study area was performed and non-vegetated areas were excluded by using decision tree method. Since the same texture feature in each band had a certain autocorrelation, the principal component analysis method was used to reduce the dimension. In the end, 49 features including original band, vegetated band, texture feature could be achieved, then 3 models with different input which were classified by random forest method could be set up. The result showed that the model which used original band, vegetation index and decreased dimension texture feature had the highest accuracy. The total classification accuracy and Kappa index was 91.03% and 0.81771 respectively. Therefore, some conclusions were figured out: (1) the classification method based on multiple features was helpful to improve the accuracy; (2) the time series characteristics of vegetation index could help improve the classification accuracy of non-main crops; (3) decreasing the dimension of texture feature could improve the efficiency and cartographic quality of the classification.

1. Introduction
Accurate land information using was the foundation of the modern agriculture. With the rapid development of precision agriculture, low-resolution images could no longer be adapted to the requirements of county monitoring [1]. For studies such as crop growth monitoring, classification, and inversion, medium and high resolutions images such as Sentinel-2A/B, SPOT, HJ-1/2, and GF-1 were increasingly being used. Wang Na et al. [2] reduced the dimensionality of GF-1 and HJ-1A data features based on the univariate feature selection method, and used the random forest method to identify and extract maize and rice in Sihong County, China. The results showed that overall classification accuracy reached 97.07% with the corresponding Kappa coefficient being 0.96. Liya et al. [3] developed a single-class classifier based on Sentinel-2 images to monitor the dynamics of fallow land. The results showed that the seasonal fallow extent can be mapped with $>92\%$ accuracy both the summer and winter seasons. Domestic research on crop classification had focused on small areas (e.g. farms) [4] or on the flat northeastern plains [5] where the influences were controllable. High-precision imagery was primarily used to study crop classification at the county scale, but such imagery was expensive. Sentinel-2 image was one of the higher precision images that currently available for free. Sentinel-2 was a wide-swath, high-resolution, multi-spectral imaging mission [6]. Because of the advantages of space and time,
Sentinel-2 images were increasingly being used in agriculture-related research. In this paper, Fengqiu County, Henan Province was used as the study area, to explore the classification effect of Sentinel-2 image data at the county scale.

2. Another section of your paper

2.1. Study Area
This study focused on an area of circa 1226.5 km² in the northeast of Henan. The Yellow River flows from west to east in the southern part of the county [7]. It had a warm temperate continental monsoon climate, with an average annual temperature of 13.5°C-15.5°C. With an annual rainfall of 615.1 mm and a frost-free period of 214 days, the area was ideal for agriculture.

Wheat and maize were the main crops grown in the region. Maize was planted in mid to late June and harvested in early October. It grows for nearly 4 months. In some areas, cash crops such as peanuts, soybeans and sweet potatoes were planted after the wheat harvest. In addition, honeysuckle was one of the specialty cultivation industries of the region and had been cultivated for 1500 years. It’s national honeysuckle production site [8]. Honeysuckle was a perennial semi-evergreen twining and stoloniferous plant. The honeysuckle picking season was from late May to mid-October.

2.2. Sentinel-2 Data
ESA launched the first Sentinel-2 (called 2A) polar-orbiting satellite in June 2015. It carried the Multi-Spectral Instrument (MSI), having four bands at 10 m, six bands at 20 m, and three bands at 60 m spatial resolution. The latter were dedicated to atmospheric corrections and cloud screening. It had a swath width of 290 km by applying a total field-of-view of about 20°.

In this paper, Sentinel-2 images of five temporal phases were selected based on growth of crops and image quality (Table 1) [9]. The study area was covered by two-field images coded as T50SKD, T50SKE, as shown in Figure 1. For most dates the study area and its surroundings were cloud-free. These images were atmospherically corrected using the SEN2COR procedure available in the Sentinel-2 SNAP (Sentinel Application Platform) toolbox, converting top-of-atmosphere (TOA) reflectances into top-of-canopy (TOC) reflectances. Resampling, image stitching, cropping, and format conversion were performed in SNAP. The coordinate system was WGS 1984.

| Number | Platform | Cloud Cover | Acquisition Date |
|--------|----------|-------------|------------------|
| 1      | SENTINEL-2B | 0.92%       | 2019-06-02       |
| 2      | SENTINEL-2A | 0.55%       | 2018-07-07       |
| 3      | SENTINEL-2A | 7.57%       | 2019-08-16       |
| 4      | SENTINEL-2A | 1.78%       | 2019-09-05       |
| 5      | SENTINEL-2B | 0.81%       | 2018-09-30       |

Figure 1. Remote sensing image map of Fengqiu County
2.3. Reference Data
To obtain a sample set of the major crop types, two field surveys were conducted in July and September 2019. To improve classification effect, crops such as watermelons, yams, vegetables, and lawns were classified as other crops, and construction and bare land were classified as non-vegetated. A shapefile file of field survey points with their location (longitude and latitude), land cover types and photos were obtained using ArcGIS. Finally, a total of 670 samples were selected, including 150 for maize, 75 for peanuts, 50 for sweet potatoes, 50 for soybeans, 60 for honeysuckle, 80 for forest fruits, 30 for rivers, 15 for ponds, 55 for other crops, and 75 for non-vegetation.

3. Methods
3.1. Feature selection and Classification feature sets
In this paper, the spectral band of B2, B3, B4, B5, B6, B7, B8, B8a, B11, B12 from Sentinel-2 images were selected to participate in the classification of features in the study area. In mid-June, autumn crops such as maize and peanuts were sown, and the vegetation index slowly increased. From August to September, the crops were flourishing and the ground was more covered. The vegetation index values were highest at this time. The surface soil reflectance spectrum had little effect on crop classification. The vegetation index values were highest at this time. In mid-to-late September, when the crops were mature and harvested, the vegetation index decreased significantly. Therefore, the image on September 5 was selected as the best time for spectral analysis. The spectral reflection curves for different crops were shown in Figure 2(a)

The vegetation index was a combination of different wavelengths of remotely sensed imagery. It was able to reflect the phenological and spectral characteristics of different vegetation types. NDVI (Normalized Difference Vegetation Index) was often used in remote sensing image classification. However, NDVI was prone to saturation in the high value area [10], and was easily affected by the soil background in the low value area. Therefore, Enhanced Vegetation Index (EVI) with atmospheric correction factor and Modified Secondary Soil-adjusted Vegetation Index (MSAVI2) with soil background control were selected. In addition, two vegetation indices NDI45 (Normalized Difference Index 45) and RENDVI (Red Edge Normalized Vegetation Index) [11] were also used in the study, which consist of red-edge bands. The vegetation index formula corresponding to the Sentinel-2 band was shown in Table 2. The time series curves were shown in Figure 2(b-f).

| Number | Index     | Formula                                                                 |
|--------|-----------|-------------------------------------------------------------------------|
| 1      | NDVI      | \( \frac{B_5 - B_4}{B_5 + B_4} \)                                      |
| 2      | EVI       | \( \frac{2.5 \times (B_8 - B_4)}{(B_8 + 6 \times B_4 - 7.5 \times B_2 + 1)} \) |
| 3      | MSAVI2    | \( \frac{2}{(2B_8 + 1) - \sqrt{(2B_8 + 1)^2 - 8(B_8 - B_4)}} \)          |
| 4      | NDI45     | \( \frac{B_5 - B_4}{B_5 + B_4} \)                                      |
| 5      | RENDVI    | \( \frac{B_5 - B_3}{B_5 + B_3} \)                                      |
Texture information in remote sensed images contained important spatial structure information and basic features of the image, which were important for image analysis. In addition, the texture features were also highly resistant to noise. The higher the image resolution, the finer the textural features. However, it might also mean higher costs.

In this paper, four 10-meter bands, including B2, B3, B4, and B8, were selected for texture feature extraction. The nine most commonly used features were calculated using the co-occurrence matrix, including contrast, dissimilarity, uniformity, second-order moment, maximum probability, entropy, mean, variance, and correlation. A total of 36 texture features were extracted. Since there were some autocorrelation of the same texture features in each band, PCA (principal component analysis) was chosen to process the texture information. As shown in Figure 3, two principal components, M1 and M2, were obtained by performing PCA on the mean texture features of the four bands. These two principal components retained 99.56% of the total amount of information, which were sufficient to reflect the mean texture information of the four bands. In the following analysis, the texture features of the corresponding bands could be replaced by M1 and M2. Similarly, the variance was analysed to obtain two principal components V1 and V2, which retained 99.24% of the total information. The correlation was optimized to obtain the principal component C1, which accounted for 97.41% of the total information. The rest of the texture features were analysed in the same way. Finally, a total of 14 texture features were obtained, reducing the amount of data by 61.1%.

**Figure 2.** Spectral graph of 5 September and time series curves of multi-temporal vegetation index system

**Figure 3.** PCA of texture features
3.2. **Classification algorithm**

RF (random forest) was an ensemble learning technique composed of multiple decision trees based on random bootstrapped samples of the training data. The output was determined by a majority vote of the results of decision trees. The random forest algorithm was well suited for the classification of high-dimensional features. The crop type was used as a row attribute. The type of classification feature was used as a column attribute. The corresponding image spectral feature values, vegetation index, and texture feature of the crop were used as attribute values to create a sample dataset. Finally, RF was used for training and learning.

3.3. **Classification process and accuracy assessment**

First, Sentinel-2 images were pre-processed. Then the spectral reflectance curve and the vegetation index (VI) time series curve was constructed based on vegetation samples. Optimal temporal reflectance image was selected. Next, the main band texture feature set was extracted, and PCA was performed to achieve feature dimensionality reduction. Finally, optimal temporal original band, VI time series and texture features were combined as the classification features.

Based on the idea of hierarchical classification, non-vegetated land classes in the study area were removed using the decision tree classification method. Rivers and ponds were then extracted because they were so distinctive. Finally, the areas covered by vegetation were obtained. Further, the classification system of vegetation areas was identified as seven feature types: maize, wood, peanut, soybean, sweet potato, honeysuckle, and other crops. Three classification feature models were constructed based on the set of previous features. The original band features were included in Model I. In the Model III, the time series characteristics of vegetation index were added on the basis of Mode I. All extracted features were included in Model III. Different sets of classification features and samples were input into the random forest classifier together for training and learning respectively. Finally, accuracy validation and comparative analysis of the classification results of different models were performed. The flow chart of the study was shown in Figure 4.

Confusion matrices was used for classification accuracy evaluation. Various evaluation indexes could be obtained by using the confusion matrix. Kappa coefficient, overall accuracy (OA), drawing accuracy (PA) and user accuracy (UA) were selected for accuracy evaluation calculation.

![Figure 4. Flow chart of study](image-url)
4. Results and analysis
The final classification results were shown in Table 3. The overall classification accuracy was 82.53%, 89.33%, and 91.03%, respectively. The Kappa coefficients were 0.7832, 0.8545, and 0.8771, respectively. Among them, the third classification models had the highest accuracy. It was shown that the use of Sentinel-2 images for county vegetation classification was feasible. Classification accuracy could be improved by increasing the number of classification features within a certain range.

As shown in Table 3, maize and woodland were identified with the highest accuracy, followed by peanut. The other crops were identified with lower accuracy. It was due to the fact that maize was the main crop in the study area. Moreover, maize was more intensively farmed. The results obtained by using the model II classification clearly showed that the classification accuracy of non-main crops has improved. The PA and UA of honeysuckle improved by 12.37% and 7.34% respectively, sweet potato by 7.03% and 2.31%, soybean by 13.1% and 4.34%. With the addition of texture features, the classification accuracy was further improved and the mapping quality was also greatly improved. As shown in Figure 5, the results obtained by Model I (Figure 5a) as a feature set were fragmented and the classification accuracy was not high. Using Model II (Figure 5b) to classify, small spots in the image were significantly reduced. Furthermore, the image details were clearer and more beautiful by the classification of model III (Figure 5c).

| Model | PA       | UA       | Model | PA       | UA       | Model | PA       | UA       |
|-------|----------|----------|-------|----------|----------|-------|----------|----------|
| Model I | 94.43    | 93.52    | Model II | 94.57    | 95.41    | Model III | 95.92    | 96.9     |
| Maize       | 87.92    | 91.93    | Wood           | 83.48    | 84.51    |       | 95.25    | 94.07    |
| Peanuts    | 73.40    | 77.60    | Sweet potato   | 80.43    | 80.91    |       | 81.22    | 83.04    |
| Soybean    | 70.74    | 82.53    | Honeysuckle    | 80.21    | 81.42    |       | 83.19    | 84.65    |
| Other      | 80.91    | 81.32    | Other          | 80.68    | 82.62    |       | 84.68    | 86.28    |

**Overall accuracy**

- Model I: 82.53%
- Model II: 89.33%
- Model III: 91.03%

**Kappa**

- Model I: 0.7832
- Model II: 0.8545
- Model III: 0.8771

As shown in Figure 6, it was the spatial distribution map of the study area in autumn using model III. Fall maize was planted most extensively in Feng Qu County, accounting for 68.48% of the total vegetation area. Peanuts were mainly distributed in the beach area south of the Yellow River and bordering Yanjin County in the north, and there was a small distribution in Huangling Town, with planting area accounting for 8.18% of all vegetation area. Soybeans were mainly grown in the Yellow River beach area, concentrated near Lizhuang Town, with a small distribution in Chenqiao Town. It accounted for 8.18% of all vegetation area. Honeysuckle was distributed throughout the county, which accounted for 3.84% of all vegetation area; Sweet potato cultivation area was small. It is mainly concentrated near Hezhai village, Zhucunpu village and Jiangzhai village in the southeast of the county.
Other small crops were more scattered, accounting for a total of 0.74%. Overall, the spatial distribution of each crop type was macroscopically consistent with the local crop distribution, and small area features could be better distinguished. It showed that the classification of sentinel-2 images could better identify small plots. Using multi-temporal different feature sets could improve the classification accuracy of features.

Figure 6. Classification results of image

5. Conclusions
Fengqiu County, Henan Province was used as the study area for this paper. The data source was Sentinel-2 images of multiple temporal phases in 2019. Sentinel-2 images were used to study the effect of classifying fall crops within the county. A total of 49 feature indicators were extracted from the original band feature, time-series vegetation index feature, and texture feature. Then three classification models were constructed based on different feature types. Using a combination of decision trees and random forests, a classification map of land use in the county was obtained and the classification results were validated. The result shows that the model which used original band, vegetation index and decreased dimension texture feature had the highest accuracy, the total classification accuracy and Kappa index was 91.03% and 0.81771. Therefore, some conclusions were figured out: (1) the classification method based on multiple features was helpful to improve the accuracy; (2) the time series characteristics of vegetation index could help improve the classification accuracy of non-main crops; (3) decreasing the dimension of texture feature could improve the efficiency and cartographic quality of the classification.

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