Object-based multi-features Wetland classification method of GF-2 PMS imagery

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Abstract. Wetland plays an important role in the earth's ecosystem. However there are still a lot of problems to classify and extract wetlands through high-resolution satellite imagery. We propose an object-based multi-features wetland classification method of GF-2 PMS imagery, taking Yuanjiang, Hunan Province as the study area, selecting multi-dimensional object features including spectral, geometric, terrain and texture features to train the CART classifier and evaluate the accuracy of the classification results. The results show that the method can obtain accurate wetland classification results, which provides technical reference for wetland classification based on GF-2 PMS imagery.

1. Introduction

Wetland is an important part of the earth natural ecosystem and has the reputation of being the kidney of the earth. It is a key task for mankind to protect wetland resources, which requires meticulous and accurate wetland classification. Traditional remote sensing wetland classification is mainly based on medium-resolution multispectral images [1]. Studies have shown that Landsat (TM) 2–4 bands are helpful for detecting understorey vegetation, and relatively bands 5 and 7 are helpful for identifying water and freshwater swamps. The Landsat 8 satellite launched in 2013 has greatly improved the accuracy of wetland classification, but this type of data is difficult to distinguish small and medium-sized wetland plots. Meter-level high spatial resolution multispectral images represented by GeoEye, WorldView and GF series can accurately identify broken wetland blocks [2, 3]. With high spatial accuracy and low cost, they provide a reliable source of wetland classification data. However, due to the finer texture and geometric information of high-resolution multi-spectral imagery, the corresponding classification work often has the problem of "salt and pepper" noise and "same objects with different spectra, and different objects with the same spectra" problem [4]. Therefore, we propose an object-based wetland classification method of GF-2 PMS imagery to solve the problem.
2. Study area and data sources

2.1. Study area
Yuanjiang City is adjacent to the West Dongting Lake, which connects the four rivers of Xiang, Zi, Yuan and Li, and is named after the place where the Yuan River flows into Dongting Lake, as is shown in Figure 1. The city has a resident population of 697,700. It has a subtropical humid monsoon climate with an average annual temperature of 16.9°C and an average rainfall of 1322mm. The city is surrounded by lakes on three sides, the river network is densely covered with broken terrain, and the tidal flats and lakes are densely covered. It is a typical Dongting Lake wetland city with moderate scales, which can be used as a typical research area for wetland classification.

2.2. Data sources
Select the GF-2 PMS imagery taken on March 27, 2018 was selected as the source data, including panchromatic band and multi-spectral band, complete geometric correction and radiometric correction to ensure the accuracy of the imagery (Figure 1). The auxiliary data includes the boundary of the study area and DEM data with a precision of 30 meters.

In addition, 300 sampling points were manually located based on field survey data and GOOGLE EARTH historical images. Randomly select 200 training samples, and the remaining 100 are used as accuracy evaluation samples. There is no overlap between the two types of samples.

Figure 1. Overview of the study area.
2.3. Preprocessing
The GF-2 PMS image contains 1 panchromatic band and 3 multispectral bands. By ENVI software, geometric corrections were performed on panchromatic and multispectral data respectively, and the cubic convolution interpolation method was used in the orthorectification experiment. Image registration ensures that the displacement deviation of panchromatic and multi-spectral images is smaller than a single multi-spectral pixel by manually selecting 30 control points with the same name.

The fusion of panchromatic and multispectral images uses the Gram-Schmidt method, which combines the radiation information of the multispectral band with the high resolution of the panchromatic band to obtain a multispectral image with a spatial resolution of 1 meter. Then perform absolute calibration and FLAASH atmospheric correction on the fused remote sensing image. The calibration coefficient and spectral response function are provided by the China Resources Satellite Application Center (http://www.cresda.com/CN/Downloads/dbcs/index.shtml). The image is cropped to obtain the preprocessed image of the study area.

| Categories          | Description                                      |
|---------------------|--------------------------------------------------|
| Lake wetland        | Permanent lakes.                                |
| Paddy wetland       | Fields where aquatic crops such as rice are grown.|
| Pond wetland        | Aquaculture ponds, artificial water landscape.   |
| Dry farming         | Fields where xerophytic crops are grown.         |
| Green space         | Orchards, pastures, plantations and urban green spaces. |
| Building            | Land and internal roads covered by buildings such as urban and rural settlements, independent settlements and factories. |
| Bare land           | Bare land or land with less than 5% vegetation coverage. |
| Road                | Urban paved roads covered with concrete or asphalt. |

3. Methodology

3.1. Classification system
The establishment of a classification system is the prerequisite for wetland classification [5]. Based on the distribution of wetlands in Yuanjiang City and the spectral characteristics of the source data imagery, a wetland classification system has been developed (Table 1).

| Features          | Description                                           |
|-------------------|-------------------------------------------------------|
| Spectral Value of each band | Band1, band2, band3 and band4 |
| Customized        | NDWI, NDVI, DVI and RVI                                |
| Geometric Shape   | Border index and shape index (unit: pxl)              |
| Range             | Area, perimeter, width and length/width (unit: pxl)   |
| Location          | The distance from the center of object to 4 each boundary (unit: pxl) |
| Texture           | GLCM homogeneity, contrast, dissimilarity, entropy, mean and StdDev |
| Terrain           | DEM (unit: m)                                         |
3.2. Classification features
Use the multi-scale segmentation method to segment the imagery to be classified [6], and a large number of patches are the objects that need to be classified. The spectral, geometric, texture, and terrain features of the objects are extracted for high-precision classification of land [7]. The feature attributes for classification are shown in Table 2.

According to the topography, climate and hydrological characteristics of Dongting Lake wetland, one water body index and three vegetation indexes are selected to characterize the characteristics of the object [8]. Spectral features include 4 band values of the source data after preprocessing, and 4 custom spectral indices, namely: Normalized Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI) and Ratio Vegetation Index (RVI), defined as follows:

\[
\text{NDWI} = \frac{\text{GREEN} - \text{NIR}}{\text{GREEN} + \text{NIR}}
\]
\[
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}
\]
\[
\text{DVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}
\]
\[
\text{RVI} = \frac{\text{NIR}}{\text{RED}}
\]

where \text{RED}, \text{GREEN} and \text{NIR} are band value of each object.

The geometric features include the shape feature, range feature, and location feature of the object, and 30-meter accuracy DEM elevation data of each object is extracted and used as a topographic feature for classification. A total of 6 texture features based on gray level co-occurrence matrix (GLCM), which are commonly used in object-based classification and have high correlation, are selected for texture features, which are selected based on the principal component analysis method. In order to reduce noise and avoid the salt and pepper effect, a $3\times3$ scale moving window is selected through multiple experiments with a step size of 1. The gray-level co-occurrence matrix is used to calculate the texture features of the imagery in 6 omnidirectional directions, and a total of 24 in 4 bands are obtained. Experiment shows that after adding customized spectral features and texture features, the optimal separation distance of the classification samples increases from 2.04 to 2.12.

3.3. Classification method
Based on the object-based imagery classification principle, after completing the multi-scale segmentation of remote sensing imagery, the extracted classification features are used as the training data set, and the CART (Classification and Regression Tree) classifier based on the GINI index is trained to conduct multi-scale and multi-feature experiments [9, 10]. Its expression is as follows:

\[
\text{Gini}(D, A) = \left| \frac{D_1}{D} \right| \text{Gini}(D_1) + \left| \frac{D_2}{D} \right| \text{Gini}(D_2)
\]

where \text{Gini}(D, A) is the GINI index of set \( D \) under the condition of known characteristics \( A \). If the value of \( \text{Gini}(D, A) \) is larger, the uncertainty of the sample is also greater, so the characteristic that satisfies the minimum value of \( \text{Gini}(D, A) \) is going to be selected.

The CART decision tree algorithm performs Boolean operations on the branch nodes. If the judgment condition is true, the left branch of the node, otherwise, the right branch, and the operation obtains the binary decision tree. When the number of layers of the decision tree reaches the preset maximum value, or the samples in all leaf nodes belong to the same category or the number of samples is 1, the CART decision tree algorithm stops growing, and the training of the classifier is completed.

4. Results and discussions
4.1. Results of classification
The classification result of the study area is shown in Figure 2. Various large and small lake wetlands in the study area have been effectively identified; paddy field wetlands are widely distributed on the north and southeast sides of the construction area, which is the largest wetland category; pond wetlands are
mainly distributed in the east of the study area. In particular, the results of small wetlands by this classification method conform to the actual distribution.

4.2. Precision analysis

The accuracy evaluation of the classification results uses the Khat method based on the confusion matrix, and uses the sample points constructed in 2.2 of the paper to select 100 as the accuracy verification samples [11]. The segmentation pattern obtained by the imagery segmentation is assigned based on the verification sample to construct the TTA Mask inspection pattern and the classification accuracy is evaluated with pixels as the statistical unit.

The results show that the overall accuracy of the classification results obtained by this method is 85.01%; the Kappa coefficient is 0.8219. Among all wetland categories, the maximum user accuracy is 91.23% of lake wetlands, and the minimum is 80.07% of pond wetlands; the maximum mapping accuracy is 89.22% of lake wetlands, and the minimum is 83.65% of paddy wetlands. Among all non-wetland categories, the maximum user accuracy is 84.50% of bare land and the minimum is 78.68% of green space; the maximum mapping accuracy is 90.19% of green space, and the minimum is 79.64% of bare land. Because this method is more sensitive to water, the extraction accuracy of wetland is significantly higher than that of other classifications of land.

Using pixel-based maximum likelihood classification method in ENVI software to conduct a control experiment, use the 200 sample points (mentioned in section 2.2) as the training sample, and the classification features are the spectral features in Table 2, including value of 4 bands and 4 customized spectral features, the comparison of the local classification results of the two is shown in Figure 3 [12]. The overall total score accuracy of the control experiment group is 74.26%; the Kappa coefficient is
The overall total score accuracy of the control experiment group was 74.26%; the Kappa coefficient was 0.7092. Therefore, the classification accuracy of our proposed method is much higher than that of the experimental group.

![Comparison of partial results of the two classification methods.](image)

**Figure 3.** Comparison of partial results of the two classification methods.

### 5. Conclusion
From a partial point of view, the classification accuracy of the CART method in roads and building land types is significantly higher than that of the MLC method. From an overall point of view, our classification method combines the advantages of multi-features and CART two theories, and the overall classification accuracy of the classification in the experimental area reaches 85.01%; the Kappa coefficient is 0.8219, and the constructed wetland classification method is based on spatial consistency and in terms of overall classification accuracy. By adding texture features and custom spectral features, the separation of the classified samples is improved, compared with other object-oriented wetland classification methods, the proposed methods have obtained more accurate and credible classification results.

The method still has the following limitations: First, the selection process of training samples is too complicated, and certain prior knowledge is required to select the classification samples, which requires professionals to operate and spend a lot of time; Secondly, the calculation time of this method is too relatively long to be suitable for large classification areas. It can be considered to use machine learning and neural network methods to improve the selection process of training samples, increase the degree of automation of the method, and the classification process to raise computational efficiency based on the principle of parallelism.

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