Sub-urban land classification using GF-2 images and support vector machine method

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Abstract. Remote sensing classification is an important part in the process of extracting effective image information and research the foundation of land cover change. While traditional remote sensing image classification methods have some problems on low accuracy and uncertainty, machine learning algorithms are gradually applied to remote sensing classification. In this paper, support vector machines (SVM) method with high training speed and low computation burden is adopted to classify land cover based on GF-2 image, which is the domestic optical remote sensing satellite with high spatial resolution. The results show that: The overall classification accuracy by SVM is achieved 72.59% and the coefficient of Kappa is 0.65. The classification map is highly consistent with the original image, especially higher classification accuracy of cropland and tree. Partial regions were misclassified as shadow that didn’t reflect the real land objects. As a whole, there is favorable classification quality using SVM method and GF-2 multispectral bands.

1. Introduction
Land cover has an important impact on regional water cycle, environmental quality and biodiversity. Remote sensing data can directly record land cover information of the surface. Remote sensing data have constantly given us valuable information for dynamic change applications such as environmental changes, urban sprawl, land cover change, and so on [1-3]. Appropriate correlation analysis tools can help us better understand their insights and timely map land use with less labor.

Classification based on remote sensing is one of the key techniques of image interpretation. Speed and accurate automatic classification algorithm of remote sensing is the key to dynamic monitoring, evaluation and prediction of environment. Due to the large amount of data and high dimension of remote sensing images, as well as the diversity of spectral characteristics and distribution characteristics of different ground objects, the common classification methods have great limitations. Meanwhile, because of the fragmentation and diversity of urban land classes, it is difficult to obtain relatively sufficient and complete sample sets and prior knowledge. Therefore, the classification of sub-urban land faced with many fuzzy objects through lack of self-learning mechanism of statistical parameter classification method.

Combined with rapid development of information technology, remote sensing data get more and more information. Among many machine learning algorithms, support vector machines (SVM) are known to be one of the most effective classification algorithms. It is a general learning methodology developed on the basis of Statistical Learning Theory (SLT) [4]. Moreover, with the increasing complexity of remote sensing data, support vector machine (SVM) framework has been greatly expanded [5,6]. In recent years, SVM algorithm has been widely used in remote sensing image
classification. It can seek the best compromise between the complexity of the model and the learning ability based on the limited sample information, which can obtain the best generalization ability. It is superior in processing small sample, high dimension and nonlinear remote sensing image. Zhu et al. (2002) based on ASTER sensor data proved high performance on convergence, training speed and classification accuracy using SVM algorithm [7]. Bruzzone et al. (2006) proposed an incremental SVM for semi-supervised classification of remote sensing images. Learning in a small sample is more advantageous [8]. Qian et al. (2015) compared the performance of four machine learning classifiers SVM, normal Bayes (NB), classification and regression tree (CART) and K nearest neighbor (KNN) to classify very high resolution images. The result showed that SVM and NB were superior to CART and KNN, particularly for the most commonly-used SVM classifier [9]. Qiao et al. (2017) used Maximum Likelihood Classifier (MLC) and SVM to classify shadow pixels into different land cover types. The results of SVM were verified and find to be consistent with the ground truth values [10]. Zhang et al. (2018) employed SVM algorithm to classify impervious surfaces based on temporal characteristics by seasonal times-series remote sensing imagery. It could accurately map seasonal urban surface dynamics [11].

The rapid development of high-resolution sensor technology provides more accurate location and higher recognition rate of ground objects for remote sensing survey of urban land, thus expanding the depth and breadth of application of remote sensing information. With the development of economy and urbanization, a new special interspace generated in this zone, which was the urban-rural ecotone. Therefore, sub-urban land classification has received widespread attention from high-resolution satellite images. As a high-resolution civil optical remote sensing satellite developed in China, GF-2 satellite effectively improves the comprehensive observation efficiency of China's satellites. Based on SVM algorithm, this paper selects experimental samples for training and classifies GF-2 images into ground objects. The results show that this method has high classification accuracy and spatial stability.

2. Data and methods

2.1. Study area
The study area is located in Henan Province, China (Figure 1). Typical objects in the area include building, road, tree, grass and cropland. It has a warm temperate and sub-humid monsoon climate with abundant thermal resources and abundant sunshine. It is dry and sandy in spring, hot and rainy in summer, sunny in autumn and cold and rainy in winter. The average annual temperate is 15°C, the average annual precipitation of 700 mm.

2.2. Data sources and pre-processing
GF-2 data is the Chinese civilian optical remote sensing satellite with a resolution superior to 1m and equipped with two high resolution scanners, 1 m panchromatic and 4 m multispectral, respectively. GF-2 satellite was successfully launched on August 19, 2014 [12]. The main users are land resources, urban-rural development and forestry. Detailed payload parameters are showed in Table 1.
Figure 1. True colour image of study area with GF-2 (R-red, G-green, B-blue; Spatial resolution 1m).

Table 1. Payload parameters of GF-2 satellite.

| Spacecraft Payload | Bands | Spectral range (μm) | Spatial resolution (m) | Swath width (km) | Scroll angle (°) | Revisit interval (days) |
|--------------------|-------|---------------------|------------------------|------------------|-----------------|------------------------|
| Panchromatic camera| 1     | 0.45-0.90           | 1                      |                  | ±35             | 5                      |
|                    | 2     | 0.45-0.52           | 4                      | 45 (2 cameras)   | ±35             |                        |
| Multispectral camera| 3    | 0.52-0.59           | 4                      |                  | ±35             | 5                      |
|                    | 4     | 0.63-0.69           |                        |                  | ±35             |                        |
|                    | 5     | 0.77-0.89           |                        |                  | ±35             |                        |

GF-2 data was acquired on 16 February 2017 containing both panchromatic and multispectral bands. The pre-processing of GF images included radiation calibration, atmospheric correction, orthorectification and data fusion. Because electromagnetic wave is affected by the solar position, angle conditions of the sensor and atmospheric conditions in the process of atmospheric transmission and sensor measurement, the target radiation amount measured by the sensor is inconsistent with the actual radiation amount of ground objects. So the radiation distortion of remote sensing image not only reduced the image quality, but also affected the application of image analysis. Radiometric calibration was the process of eliminating radiation distortion in remote sensing image. Atmospheric correction was performed using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module based on the improved MODTRAN4+ model. The atmospheric model was set as the mid-latitude winter model. The aerosol type was set to urban type. Atmospheric visibility was set at 40 km, and the average altitude was 200 m. The absolute radiation calibration coefficient and spectral
response function were published by China Centre for Resources Satellite Data and Application. The
digital number (DN) of the original image was converted to spectral reflectance value. Then, the
panchromatic and multispectral bands were geometrically corrected using the rational polynomial
coefficient (RPC) correction module based on digital elevation mode (DEM). The total error of
geometric correction and single control point error are controlled within 1 pixels. In addition, the
Gram-Schmidt Pan-Sharpening model was used to translate and sharpen the multi-spectral bands and
panchromatic bands to obtain very high-resolution (VHR) multi-spectral images with a spatial
resolution of 1 m. Image element resampling is performed by cubic convolution algorithm. Meanwhile,
the normalized difference vegetation index (NDVI) was one of the best indicators of vegetation
growth state and calculated by the VHR multispectral images. The calculation formula is as follows:

\[
\text{NDVI} = \frac{R_{\text{NIR}} - R_{\text{RED}}}{R_{\text{NIR}} + R_{\text{RED}}}
\]  

where \( R_{\text{NIR}} \) and \( R_{\text{RED}} \) represent the reflectance value with the near-infrared band and the red band of
GF-2 data, respectively.

Then, VHR multispectral image and NDVI composed into one image data. The above processes
were implemented by ENVI software.

2.3. Classification method
Classification method uses SVM [13], which is a supervised classification method based on a set of
theoretical machine learning algorithms. We operated the SVM analysis by the independent training
data, which was the important step. SVM liner classification initially separates the classes based on a
decision surface called the optimal hyper-plane, which maximizes the margin between the classes, and
the data points closest to the hyper-plane are called support vectors. Hence, SVM identifies support
vectors that have a greater ability to differentiate between classes, thereby constructing a classifier that
maximizes the separation between classes and classes. In SVM nonlinear classification, the sample is
projected into a high-dimensional linear space based on a non-linear mapping algorithm, in which the
optimal hyper-plane is generated. The classification process is simple and based on the kernel function
that replaces inner product of the feature space, in which linear methods may be applied. Common
kernel functions include linear kernel, polynomial kernel, radial basis kernel and S-shaped kernel [14].

2.4. Sampling data and accuracy assessment
Six classes were selected for the purposes of this comparison study: building, road, tree, grass,
cropland and shadow. A random sample of image pixels within the six land cover types was
performed. A total of 9041 image pixels were selected on Google earth images with high spatial
resolution. 70% of the samples are training data of SVM algorithm, and another 30% are test data of
accuracy evaluation (Figure 2). Confusion matrix is used to evaluate the accuracy of classification
results. Kappa coefficient, total accuracy, user’s accuracy and producer’s accuracy are calculated for
entire dataset and each class.
Figure 2. The distribution of training data and testing data.

3. Data and methods

3.1. Results of SVM classification

The SVM classification process is based on a kernel function, we use the radial basis function (RBF) kernel because it has proved more effective for many classification applications [15-18]. The penalty parameter was set to 1000, and the other parameters were based on the default after several tests. The image resulting from the SVM classification was shown in Figure 3. Six different classes were established: building, road, tree, grass, cropland and shadow. Based on the classification results of confusion matrix, the total accuracies were 72.59%, Kappa coefficient were 0.65. Table 2 showed that the classification of cropland and shadow were best. The producer’s accuracy and user’s accuracy were greater than 85%. The classification accuracies of tree were secondary, producer’s accuracy and user’s accuracy were 78.71% and 71.29%, respectively. Building was low, producer’s accuracy and user’s accuracy were 69.86% and 69.77%, respectively. The classification accuracy of grass and road was the lowest. User’s accuracy was both less than 70%, producer’s accuracy of grass and road was only 44.65% and 62.19%.

GF-2 image had better classification performance of cropland and tree when extracting vegetation information. GF-2 images contain near-infrared band and red band, which are sensitive to vegetation. While grass and cropland are non-dominant classes in this area, cropland class was precisely identified as higher than grass class. This could be caused by textures of cropland obviously described than grass. It showed that GF-2 performs extremely well at distinguishing between cropland class and other classes.

However, extracting road and building information is not ideal, they were misclassified to some extent, mainly due to the similarity of the spectrum. Future work will add multi-sources or features to distinguished road and building. For example, normalized digital surface model (nDSM) derived from LiDAR data will greatly classify building and road by height feature.
On general visual inspection, the classification results produced a speckled “salt-and-pepper” effect, because adjacent pixels are lacking comprehensive analysis. Further studies should compare object-based SVM algorithm or other machine learning methods to created visually acceptable depictions of the broad land cover classes present within the study area.

Table 2. Confusion matrices based on test data.

| Class       | Building_t | Cropland_t | Grass_t | Road_t | Shadow_t | Tree_t | Total | User's accuracy |
|-------------|------------|------------|---------|-------|----------|--------|-------|-----------------|
| Building_m  | 510        | 0          | 1       | 187   | 3        | 30     | 731   | 69.77%          |
| Cropland_m  | 0          | 45         | 0       | 0     | 0        | 0      | 45    | 100.00%         |
| Grass_m     | 14         | 0          | 96      | 2     | 0        | 40     | 152   | 63.16%          |
| Road_m      | 156        | 0          | 8       | 380   | 1        | 30     | 575   | 66.09%          |
| Shadow_m    | 15         | 0          | 2       | 4     | 412      | 39     | 472   | 87.29%          |
| Tree_m      | 35         | 0          | 108     | 38    | 26       | 514    | 721   | 71.29%          |
| Total       | 730        | 45         | 215     | 611   | 442      | 653    | 2696  |                 |
| Producer's accuracy | 69.86% | 100.00% | 44.65% | 62.19% | 93.21% | 78.71% |

Figure 3. Land cover mapping based on the SVM algorithm.

3.2. Area distribution of sub-urban lands
Areas of different land cover were calculated with classification results (Table 3). Area of building was 221446 m² accounting for 7.04% of region, which was the largest area. Area of tree was less than building and accounted for 25.81% of region. Because of the height of building in the city, urban land
generated a lot of shadow area in direct sunlight. Area of shadow was 129130 m$^2$, accounting for 21.60% of region. The shadow classification included road, tree and grass. The road area was 75890 m$^2$, accounting for 12.7% of region. Grass land area was 15417 m$^2$ accounting for 2.58%. The area of cropland was least than other sub-urban lands, only accounting for 0.27%.

Based on VHR multispectral images there is a shadow effect of classification results in our experiment area. This finding was consistent with other studies [19]. The work presented will further be improved by incorporating LiDAR for the land cover classification. LiDAR could provide elevation information and eliminate the shadow problem.

### Table 3. Area and proportion of sub-urban land classification.

| Classification | Area (m$^2$) | Percent (%) |
|----------------|-------------|-------------|
| Building       | 221446      | 37.04       |
| Cropland       | 1588        | 0.27        |
| Grass          | 15417       | 2.58        |
| Road           | 75890       | 12.70       |
| Shadow         | 129130      | 21.60       |
| Tree           | 154315      | 25.81       |

Overall, compared with other VHR optical satellite sensors, GF-2 data can provide better classification mapping accuracy in sub-urban environments. Its advantage had ability to distinguish spectral differences between land covers, especially between shadow and tree. The classification accuracy of urban land cover was estimated based on QuickBird image, with a total accuracy of 69.12% and a kappa coefficient of 0.62 [20]. Hamedianfar et al. (2014) achieved the classification results using WorldView-2 imagery and the two machine learning methods, yielding overall accuracies of 72.46% and 75.69%, respectively [21].

### 4. Conclusion

In this paper, we verified the potential classification accuracy of GF-2 satellite data, and found that the classification mapping accuracy of gf-2 multi-spectral data in sub-urban zone was relatively good. SVM machine learning performed better classification in this study zone, and the total accuracy was 72.59%, Kappa coefficient was 0.65. Cropland and shadow were the best classification accuracy, followed by tree, building, and grass, road. The producer’s accuracy of cropland and shadow were more than 93%, and the user’s accuracy was more than 87%. GF-2 image had good performance in extracting vegetation information, especially in cropland and tree. However, distinguishing between building and road using GF-2 multi-spectral band and NDVI is difficult, they were misclassified. In general, region-based classifiers can improve classification accuracy. We will further study more accurate classification methods on sub-urban land classification in the future.

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