Integration of multi-classifiers in object-based methods for forest classification in the Loess plateau, China

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ABSTRACT: The object-oriented method with three integrated different classifiers was applied to classify satellite images of the forest in the Loess Plateau in China. After image segmentation, feature selection, and training sample selection, three classifiers—the support vector machine (SVM), *k*-nearest neighbour algorithm, and classification and regression tree—were used for forest classification using SPOT images as the data source. Results indicated that the object-oriented method with the three classifiers effectively extracted Chinese pine forestland, *Betula* forestland, oak forestland, shrubland, wasteland, farmland, and roads in the study area. The main segmentation parameters of scale, colour, and shape performed best when their values were set to 100, 0.9, 0.1 in forestland and 60, 0.5, 0.5 in non-forestland, respectively. In addition, SVM was the best classifier applied to the forest classification with an overall accuracy of 78% and a kappa coefficient of 0.737. This study provides a fast and flexible approach to forest classification and lays the foundation for forest management and forest resource surveys.

KEYWORDS: object-based classification, image segmentation, feature selection, remote sensing

INTRODUCTION

The vegetative land cover is an important variable in earth-system processes[1]. Forests serve a crucial function in protecting natural resources for humans and other life forms, in minimizing ecological and environmental deterioration, and in responding to the challenge of climate change[2]. Forest surveys provide the theoretical basis and technical support for analysing the status and dynamics of forest resources. They also have an important role in forecasting the change trend of forest resources and in formulating sustainable forest management plans[3]. The ability of China to manage its forest resources in a sustainable manner is challenging. In view of the advancement in the social economy, the conventional method for forest resource surveys in the country remains inherently limited and therefore fails to meet the requirements of the development of modern forestry. Remote sensing classification is one of the indispensable components of forest resource surveys, and its classification accuracy directly influences the level of applicability and practical value of such surveys. Thus improving the precision of classification is an urgent issue in the research field[4,5].

The Loess Plateau is well known for its great development potential, but the area also suffers from the highest rates of erosion in the country and is the source of most of the deposited sediments in the Yellow River[6,7]. The change in land use and land cover in this region is significant and has a great effect on the local environment and diversity of the ecosystem[8,9]. Over the last decade, various approaches have been applied in classifying the land cover of the plateau; these approaches include unsupervised classification, supervised classification, and the genetic algorithm-based decision tree classifier[6,10]. At present, only a few studies have employed the object-oriented method in classifying the remote sensing images of the forest in the Loess Plateau.

The object-based classification is widely employed in land survey and monitoring and generates many good results[11,12]. It is however rarely employed in research on forest classification. The object-based technique takes groups of pixels or 'objects' instead of individual pixels as the unit of

classification, and assigns every object in an image to a class [13]. Two basic methods can be employed for object-based classification: classification by rules and classification by training samples. In classification by rules, a classification tree based on binary recursive splitting was first developed, after which the data were divided into homogeneous groups [14]. This method is always time consuming because of repeated trials, and the rules built in one place cannot be applied in another place. In classification by training samples, stable training areas are chosen based on the experience of experts, after which a professional software is used to automatically classify the data into different classes. This process saves much time in building rules, thereby improving the efficiency and productivity of the method. The present study employs both methods for object-based classification.

This study presents the parameters to be used in object-based classification and evaluates the performance of the method in the forest classification of the Loess Plateau. Three classifiers are also compared with each other to select the best one in the forest classification of the study area.

MATERIALS AND METHODS

Study area

The Caijiachuan forest farm (latitude: $35°28'$ to $36°02'$ N, longitude: $109°48'$ to $110°12'$ E) is located in the middle of Loess Plateau, China. Caijiachuan has an area of 20 726 ha and is mostly between 1100 and 1300 m in altitude. The region has a semi-humid continental climate, with a mean annual precipitation of approximately 611 mm and a mean monthly temperature ranging from 21.8 °C in July to −5 °C in January. The soil type in this region is cinnamon and grey cinnamon soil. This region is a typical forest of the Loess Plateau and is suitable for the study of the classification of forestland by remote sensing. This area is rich in forest resources, and the dominant species include *Pinus tabulaeformis* Carr., *Betula platyphylla* Suk., and *Quercus wutaishanica* Mayr. The location of the study area is shown in Fig. 1.

Data sources and pre-processing

Four data sets were employed for the classification of the Caijiachuan forest farm. The main image, 'Satellite Pour l'Observation de la Terre' (SPOT 5) high-resolution geometric (HRG) had a resolution of 10 m in the multi-spectral bands and 2.5 m in the panchromatic band. It was purchased from
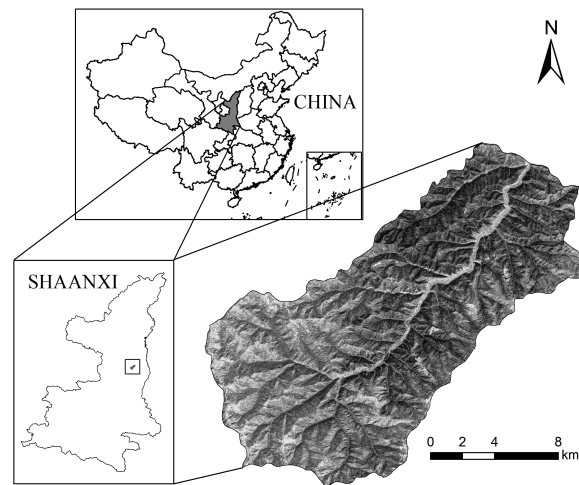

Fig. 1 Location of the study area.

Satellite Imaging Corp. (www.satimagingcorp.com) and was acquired on 18 September 2006. The advanced space borne thermal emission and reflection radiometer (ASTER) global digital elevation model data with a spatial resolution of 30 m were downloaded from website of Geospatial Data Cloud (www.giscloud.cn). The results of the forest resource survey in 2006 were also used to select the training area and to assess the classification results. The normalized difference vegetation index (NDVI) was derived from the SPOT 5 images and applied in the image segmentation.

Before implementing object-based classification, pre-processing procedures were applied for image enhancement to improve the results of image classification. The pre-processing procedures included radiometric correction, geometric correction, and resolution fusion. The enhanced image was then used in object-based classification. A flowchart of the sequence of operations is shown in Fig. 2.

Image segmentation

Image segmentation is a technique similar to computer vision and pattern recognition. This technique initially considers each pixel as an individual object, after which it merges the pixel with a neighbouring pixel with similar features, thereby producing a larger object than the original pixel. This process is repeated until the size of the objects meets the user-specified threshold [15, 16]. The object-based classification software used in this study was ECOGNITION PROFESSIONAL 8.6.4. The multi-resolution segmentation approach is a bottom-up region-merging tech-
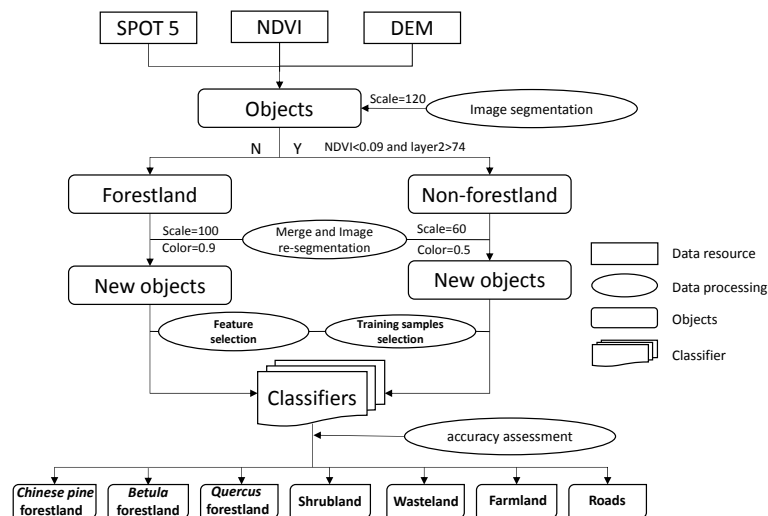
Fig. 2 Flowchart of the sequence of operations.

nique that starts with a one-pixel object[17, 18]. As one of the latest and most suitable techniques in image segmentation[19], the multi-resolution method was adopted to divide the whole area into different objects. Multi-resolution segmentation is based on four criteria: scale, colour, smoothness, and compactness[17]. Scale is the most important parameter and it affects the size of the objects and the border in the output classification map[20]. All four criteria must be optimized to obtain the best segmentation objects and to appropriately delineate the truth objects through repeated trials[21, 22].

In image segmentation, proper layers should be selected, and their importance degree must also be specified to estimate the spectral heterogeneity[20]. The heterogeneity (f) of every object is determined by the object shape and colour:

$$f = w\,h_{\text{colour}} + (1-w)\,h_{\text{shape}} \tag{1}$$

$$h_{\text{shape}} = w'\,h_{\text{compact}} + (1-w')\,h_{\text{smooth}} \tag{2}$$

where h_{colour} is the spectral heterogeneity; h_{shape} is the heterogeneity of the shape; h_{compact} is the compactness of the shape; and h_{smooth} is the smoothness of the shape. The heterogeneity of the shape is determined by the smoothness and compactness of the shape, as shown in (2). In (1) and (2), w (or w') is a weight ranging from 0–1 and is used to describe the importance of the relative variable to the results. The larger the value of w (or w') is, the higher the importance of the variable, and vice versa. The image segmentation process in this study was divided into three steps:

(i) A large scale (120) was applied in the first image

segmentation, and the pixels were merged into different objects.

(ii) The objects were then divided into forestland and non-forestland based on the classification rules. The logical expression model developed for the classification of forestland and non-forestland was as follows.
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If (NDVI < 0.09) or (layer 2 > 74),
then class = forestland;
otherwise, class = non-forestland.
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Layer 2 was the second band of SPOT image. After examining the attributes of every object (i.e., either forestland or non-forestland), the neighbouring objects with similar attributes were merged into a larger object, which was then considered the mother-object of the second segmentation.

(iii) The second segmentation was processed based on the objects obtained in Step (ii).

Different parameters were employed for the various composition and structures of forestland and non-forestland. A smaller scale than that in the first segmentation was adopted in the second segmentation to delineate the forest vegetation polygons well (Table 1).

Table 1 Parameters of image segmentation based on objects.

Segmentation parameters	Forestland	Non-forestland
Scale	100	60
Colour	0.9	0.5
Shape(compact/smooth)	0.1(0.5/0.5)	0.5(0.5/0.5)

Table 2 List of object features.

Feature category		Object features	Number of features[†]
Spectral		Mean	5
		SD	5
		Brightness	1
		Max-Diff	1
Shape		Length/width	1
		Shape index	1
Texture	GLCM	Homogeneity	5
		Contrast	5
		Dissimilarity	5
		Entropy	5
		ASM	5
		Mean	5
		SD	5
		Correlation	5
	GLDV	Entropy	5
		ASM	5
		Mean	5
		Contrast	5
Total			74

[†] The number of features was calculated using the four bands of SPOT 5 HRG after image confusion and one band of NDVI. The weight ratio of these five bands was 1:1:1:1:2. For brightness and max-diff, all the five bands were used; thus they have only one feature. Length/width and shape indices were calculated according to the shape of each object; thus they also have only one feature.

Feature selection

Much information is contained in the relationship between adjacent pixels as opposed to that in a single pixel; such information includes texture and shape, which are the key features of objects[23]. Feature selection chooses the suitable features (e.g., spectral, shape, and texture) that are used in object-based classification. Texture is a vital parameter in object-based classification[16]. The grey level co-occurrence matrix (GLCM) was computed for every object. GLCM describes the co-occurrences of the pixel values that are separated at a distance of one pixel inside the polygon by considering the combined values of four different orientations[24]. All the object features selected in this study are described in Table 2.

Training sample selection

The training samples of seven land use types, including Chinese pine forestland, *Betula* forestland, *Quercus* forestland, shrubland, wasteland, farmland and roads, were selected from the segmentation objects for training classifiers. The forest survey data in 2006 was used as reference in selecting the training samples. The training samples were equally distributed and saved as stand ESRI shape file format.

Classification using multi-classifiers

After feature space selection and training sample selection, classification was performed with multi-classifiers. The three most commonly used classifiers, *k*-nearest neighbour (KNN), support vector machine (SVM), and classification and regression tree (CART), were selected in our study.

The KNN classifier, which is also called the nearest neighbour classifier, initially calculates the average vector and the standard deviation vector of each sample and then calculates the distance of the object and the sample. A short distance means a high similarity and categorization in the type with minimum distance. However, the KNN classifier increases the classification error rate when the training samples are unevenly distributed[25]. The SVM classifier is a new learning method based on spatial statistics, which can solve small sample problems and has good generalization ability using the principles of structural risk minimization. The SVM locates a hyperplane to correctly separate the data. More details on SVM classifier theory can be found in previous studies[26, 27]. The present study uses the classification based on the SVM algorithm with the radial basis function kernel and disregards other kernels. The recursion algorithm for bisection is used in CART. This algorithm divides the current data set into two parts, and every non-leaf node has two branches in the decision tree, which is a binary tree with a terse structure[28, 29].

RESULTS AND DISCUSSION

Image segmentation

After the object was classified into either forestland or non-forestland, a small scale (60) was employed in the second segmentation for non-forestland objects in repeated trials because the scale showed an increase in landscape fragmentation. Forestland is the main landscape of the study area, and the segmentation scale (100) is 1/2 to 2/3 of the forest sub compartment. Shape and colour determine the heterogeneity of the object, and forestland and non-forestland should be given different weight values of colour and shape, respectively. The results of the image segmentation are shown in Fig. 3.
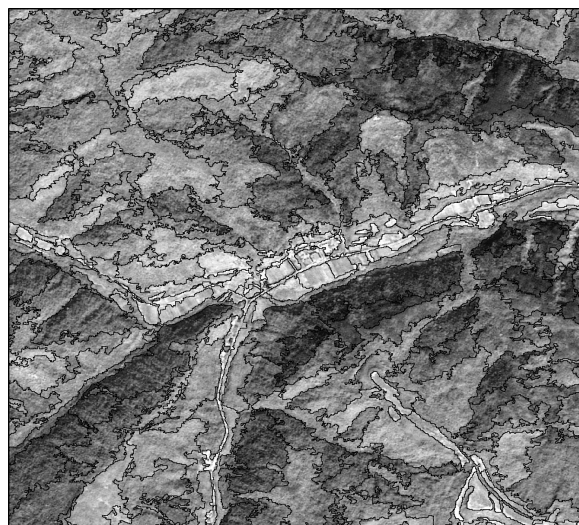
Fig. 3 Image segmentation.

Image classification and accuracy assessment

The classification results were obtained through the three classifiers with similar training samples. A comparison of the results showed that SVM was the best classifier with the most accurate result. The classification results of the three classifiers are shown in Fig. 4. To assess the classification results, a total of 243 objects were selected from the study area, see Table 3. These objects were distributed equally and were proportional to the total area of these types. The overall accuracy and kappa coefficient were used to assess the accuracy of the three classifications. The results were illustrated with comparison of the three classifiers. SVM was found to be the most accurate classifier with a total accuracy of 78% and kappa coefficient of 0.737, followed by KNN with a total accuracy of 74% and kappa coefficient of 0.712. CART was the least accurate classifier with a total accuracy of 65% and
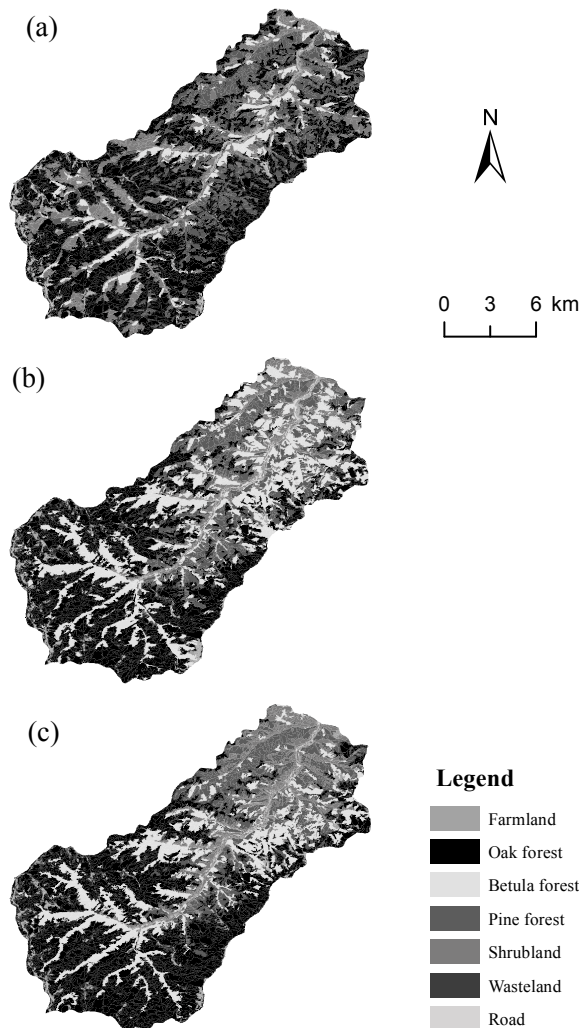

Fig. 4 Comparison of the results of the three classifiers. (a) CART; (b) KNN; (c) SVM.

kappa coefficient of 0.673.

In conclusion, the order of the three classifiers in terms of accuracy is SVM > KNN > CART. The

Table 3 Confusion matrix of the results of the SVM classifier.

Types	Chinese pine	*Betula*	*Quercus*	Shrubland	Wasteland	Farmland	Roads	Total	Accuracy
Chinese pine forest	40	3	5	2	1	0	0	51	78%
Betula forest	3	35	4	3	0	1	0	46	76%
Quercus forest	7	3	48	1	1	0	0	60	80%
Shrubs	1	1	2	18	1	1	0	24	75%
Wasteland	1	0	1	0	15	1	0	18	83%
Farmland	0	1	1	1	2	16	1	22	73%
Road	0	0	0	1	1	2	18	22	82%
Total[†]	52	43	61	26	21	21	19	243	78%

[†] Total accuracy = (40+35+48+18+15+16+18)/243 = 78%, kappa coefficient = 0.737.

results showed that the SVM classifier was more effective than the two other classifiers (KNN and CART). However, SVM also had disadvantages in terms of sensitivity to the Hughes phenomenon[26], which is common in processing widely used hyper-spectral images.

CONCLUSIONS

This study focused on each of the processes of object-based classification, including determining the optimum segmentation scale and weight ratio of every band and selecting the feature space and classifiers. The study area was divided into seven types: Chinese pine forestland, *Betula* forestland, *Quercus* forestland, shrubland, wasteland, farmland, and roads. The results led to the conclusion that the method of taking different parameters in forestland and non-forestland segmentation was better than the same. The classification results indicate that, among the three classifiers, SVM has the best performance in classifying the natural forest of the Loess Plateau. With additional details and further validation, an approach based on more classifiers and different remote sensing resource will help improve the accuracy of forest classification.

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