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A Comparison of Four Algorithms for Land-Use Classification Based on Landsat 8 OLI Image

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A Comparison of Four Algorithms for Land-Use Classification Based on Landsat 8 OLI Image

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Abstract. Accurate mapping and monitoring of land-use is essential for reasonable land management and planning. To extract land-use classes based on remote sensing images, many classification algorithms have been proposed. However, the comparison between some main supervised classification algorithms is rarely researched. This study selected the eastern fringe area of Jinan as the study area and the Landsat 8 OLI image of 2019 as data to compare the performance of four supervised classification algorithms that are MLC, SVM, ANN and RF especially. The results shown that the overall accuracy and kappa of RF is 86.2% and 0.8, and the overall accuracy and kappa of SVM is 83.2% and 0.75, and the overall accuracy and kappa of ANN is 81% and 0.72. The overall accuracy and kappa of MLC is 73.6% and 0.63. These denote that the RF can achieve the best classification result in four algorithms, followed by SVM, ANN and MLC.

1. Introduction

Along with economic development and population growth, land resources become increasingly scarce. Therefore, the researches of accurate mapping and monitoring of land-use have drawn more and more attention.

In recent decades, remote sensing technology has developed rapidly. And owing to the remote sensing images can provide low-cost, multi-source and time series observations at regional to global scales, it gradually become a primary data source to conduct Land-use classification [1]. To extract land-use classes using remote sensing images, many classification methods have been proposed. Considering the differences of machine learning strategies, these classification methods broadly fall into three categories: supervised, unsupervised, and hybrid [2]. Among these, the supervised classification method was more effective and used broadly.

The supervised classification method operated in two steps generally. Firstly, enough image training samples (class labels are known) were selected to train the classifier. And then, the classifier was used to recognize and label all pixels of image. In order to extract image information accurately, many supervised classification algorithms have been proposed, such as maximum likelihood classification algorithm (MLC), artificial neural network (ANN), decision tree algorithm (DT), support vector machine algorithm (SVM), random forest algorithm (RF), and so on [3, 4]. Although these algorithms have proved to be effective, the comparison between these algorithms is rarely researched.

Hence, this study selected four typical and frequently-used supervised classification algorithms to extract land-use information based on the same training samples and remote sensing image. The purpose is to compare the performance of four algorithms on remote sensing based land-use classification.

2. Study Area and Research Data

The study area is located in the eastern of Jinan which is the capital of Shandong Province, China (figure 1). Since the reform and opening up, China experienced a rapid urbanization process. From 2000 to 2016, driven by the real estate economy, the urban area of Jinan expanded 37% [5]. The study area is the mainly urban fringe areas of Jinan, and its land-use state is complex. Therefore, this area is suitable for comparison of different algorithms in complex land-use classification.

This study selected Landsat 8 OLI image of 2019 as the research data. The Landsat image can be downloaded freely from the United States Geological Survey website (https://landlook.usgs.gov/) and own spatial resolution of 30 meter. And it is suitable for land-use classification and has been used in many studies. In addition, the Google earth images were selected as auxiliary data in training samples collection and accuracy assessment processes.

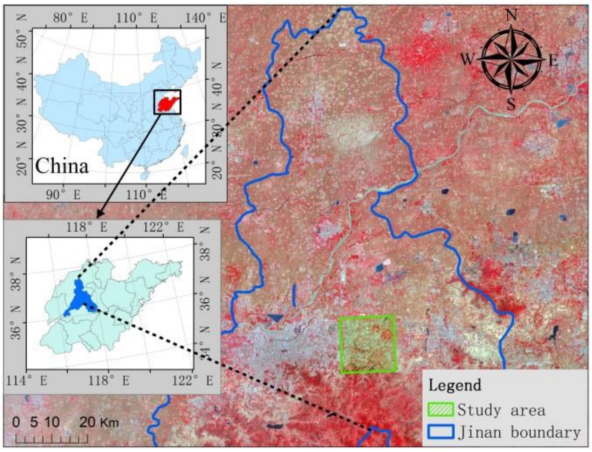

Figure 1. Geographic location of the study area.

3. Methods

3.1. Training Samples Collection

The quality of training samples is essential for supervised classification [6]. According to our knowledge about the study area, the main land-use classes in this area are forest, farmland, urban land, water body, unused land and other build-up land which mainly is village land. We collected training samples of each class with assist of Landsat origin image and Google earth images. And then, we evaluated the separability of samples between different classes by Jeffries–Matusita (JM) distance [7].

3.2 Maximum Likelihood Classfication

Maximum likelihood classification (MLC) was the first rigorous algorithm to be used with remote sensing image widely [2]. Its operation is based on the assumption that the probability distribution for each spectral class is of the form of a multivariate normal model with dimensions which equal the number of spectral bands [8]. The discriminant function of this algorithm is

$$g_i(x) = -ln|C_i| - (x - m_i)^T C_i^{-1}(x - m_i) \qquad i = 1 \cdots n \tag{1}$$

where x is brightness vector of a image pixel, m_i is the mean brightness vector for class i, and C_i is the covariance matrix of size $N \times N$, and N is the total number of spectra bands. n is the number of classes. The class of each pixel was decided by the rule:

$$x \in \omega_i \qquad if \quad g_i(x) > g_j(x) \tag{2}$$

where ω_i is spectral class i.

3.3. Support Vector Machine
Support Vector Machine (SVM) classification method derived from statistical learning theory. The first step of this method is transforming the original pixel vectors to a new set of features. And then, an optimal hyperplane that maximizes the margin between the classes is found in the feature space [9]. The purpose of vector transformation is to improve separability as much as possible. The decision function of the SVM is

$$f(x) = sign(\sum_{i=1}^{N} \alpha_i^* \, y_i K(x, x_i) + b^*) \tag{3}$$

where α_i^* are Lagrange multipliers, N is the number of support vectors that are training data for which $0 \leq \alpha_i^* \leq C$. C is a user-defined parameter that controls the tradeoff between the number of nonseparable pixels and the machine complexity. $K(x, x_i)$ is kernel function used to transform pixels vectors. The Radial Basis Function (*RBF*) kernel was used in this study. The bias b^* is a scalar computed by using any support vector.

3.4. Artificial Neural Network
The most frequently-used artificial neural network (ANN) in land-use supervised classification is the supervised Multilayer Perceptron (MLP) [10]. MLP networks generally consist of three types of layers, namely, one input layer, one or more hidden layers, and one output layer. As shown in figure 2, pixel vectors were inputted into the input layer, and then were trained with the supervised backpropagation (BP) algorithm [11] in hidden layer. Finally, the trained results were outputted through output layer.

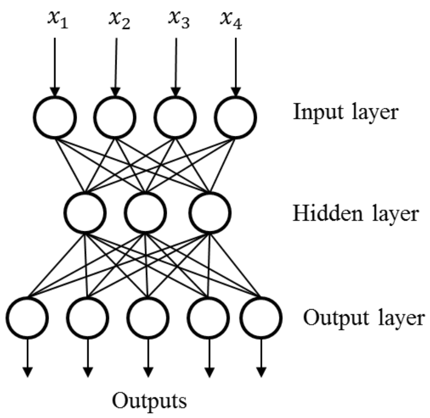

Figure 2. The structure of three-layer MLP neural network.

3.5. Random Forest
The random forest (RF) classification algorithm is an ensemble classifier that uses a set of decision trees to make a classification prediction [4]. The trees are created by drawing a subset of training samples through replacement (a bagging approach). This means that one sample may be selected several times, while others may not be selected at all [12]. Thus about two thirds of the training samples are used to train the trees and the remaining samples are used to estimate the performance of RF. The classification decision of image pixels is taken by the vote of all trees. The membership class with the maximum votes will be finally selected.

4. Results and Discussion
The accuracies of classification results were evaluated by error matrices. The classification maps and accuracy evaluation results of four algorithms were shown in figure 3 and table 1. The overall accuracy of RF is 86.2%, and it is the highest in four algorithms. The overall accuracy of MLC is 73.6%, and is the lowest accuracy. The overall accuracy of SVM and ANN are 83.2% and 81%, and obvious higher than MLC. The user's accuracy of other build-up land in MLC result is 33.6% and is

the lowest. The areas of other build-up land in MLC are obvious more than other algorithms and mixed seriously with farmland. The lowest producer's accuracy of RF is 73.3% and obvious higher than the other three algorithms which are 65.9%, 66.6% and 66.6% respectively. The lowest user's accuracy of RF is 65.9% and higher than the other three algorithms which are 57.1%, 55.2% and 33.6% respectively. These denote that the RF can achieve the best classification result in four algorithms. The performance of MLC is the worst in four algorithms. The performance of SVM and ANN is similar.

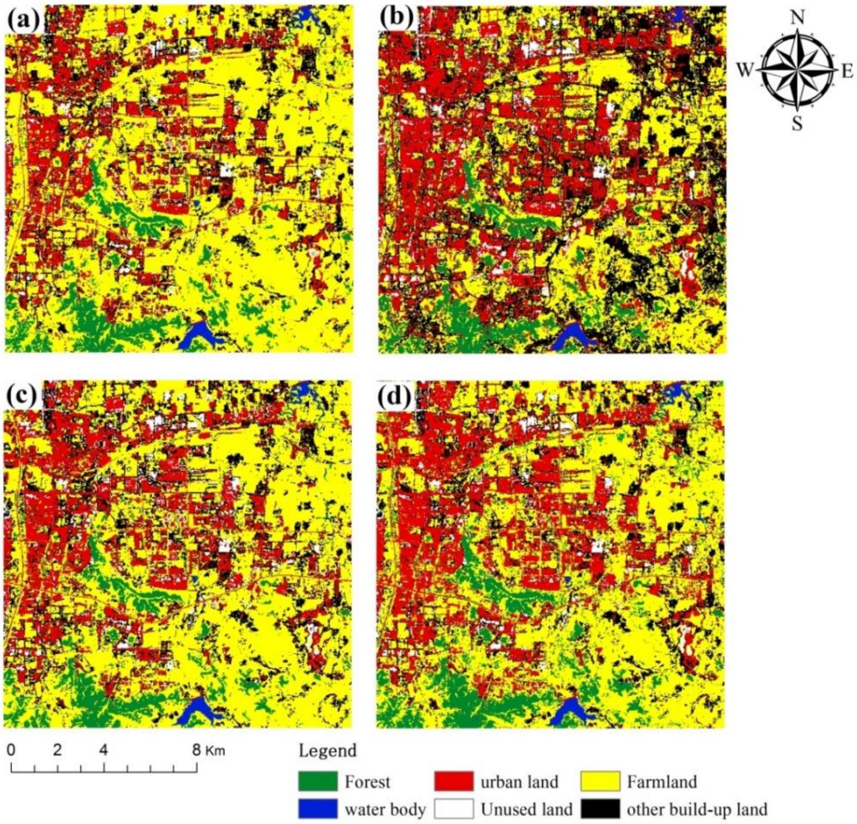

Figure 3. Classification maps of four algorithms: (a) map of ANN; (b) map of MLC; (c) map of SVM; (d) map of RF.

Table 1. Accuracy evaluation results of four algorithms, C1 denotes other build-up land, C2 denotes Farmland, C3 denotes unused land, C4 denotes urban land, C5 denotes water body and C6 denotes forest.

		C1	C2	C3	C4	C5	C6	Overall (%)	Kappa
RF	**Producer's (%)**	84.7	87.6	73.3	83.8	83.3	100	86.2	0.8
	User's (%)	68.4	91.5	84.6	93.1	100	65.9		
ANN	**Producer's (%)**	74.5	95.7	66.6	65.9	66.6	90.3	81	0.72
	User's (%)	57.1	82.7	71.4	94.4	80	77.7		
SVM	**Producer's (%)**	79.6	92.8	80	73.7	66.6	83.8	83.2	0.75
	User's (%)	55.2	87.8	66.6	93.6	80	89.6		
MLC	**Producer's (%)**	69.4	66.6	73.3	81.5	66.6	83.8	73.6	0.63
	User's (%)	33.6	89.1	68.7	86.3	100	81.2		

This study compared the four classification algorithms used image in one time point. Owing to the influence of season on the separability between different land-use classes, the overall accuracies of four algorithms were less than 90%. Thus, to improve accuracy, many studies used time series images in land-use extraction [13, 14]. In addition, the performance of each algorithm relies on optimal parameters' selection [15]. This study just compared the different algorithms, and did not research the influence of different parameters on classification performance. Thus, the relevant studies ware value to research in future.

5. Conclusion

This study selected the eastern fringe area of Jinan as the study area and the Landsat 8 OLI image of 2019 as data to compare the performance of four supervised classification algorithms that are MLC, SVM, ANN and RF especially. The accuracy evaluated results shown that the overall accuracy and kappa of RF is 86.2% and 0.8. The overall accuracy and kappa of SVM is 83.2% and 0.75. The overall accuracy and kappa of ANN is 81% and 0.72. The overall accuracy and kappa of MLC is 73.6% and 0.63. These denote that the RF can achieve the best classification result in four algorithms, followed by SVM and ANN. The classification accuracy of MLC is the worst in four algorithms.

Acknowledgments

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