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Comparison of machine learning, supervised, and unsupervised algorithms for a land cover classification in northern Mongolia

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ABSTRACT
The aim of this study is to compare the performance of machine learning approaches alongside supervised and unsupervised techniques to differentiate land cover classes in the northern Mongolia. The primary goal is to identify which of these methods can achieve the highest classification accuracy. For this analysis, we selected ten original spectral bands from Sentinel-2 data and utilized three different feature combinations. To differentiate among the available classes, we employed a support vector machine (SVM), a Mahalanobis distance classifier, and K-means clustering, assessing their relative effectiveness. In the three-band feature combination, K-means obtained the lowest accuracy at 70.08%, whereas SVM achieved 92.72%, ranking it as the most effective method. The Mahalanobis distance classifier closely followed with an accuracy of 90.36%. In the five-band combination, K-means improved its accuracy to 95.56%, surpassing earlier results, while the Mahalanobis distance achieved 95.07%, and SVM recorded an accuracy of 93.33%. In the analysis involving all ten bands, K-means again delivered the highest accuracy at 95.83%. The Mahalanobis distance classifier reached an accuracy of 93.93%, while SVM had an accuracy of 93.14%. In many cases, machine learning techniques can often outperform traditional methods. However, in this study, the traditional unsupervised technique surpassed both machine learning and supervised techniques in two cases. Thus, the results suggest that achieving high accuracy is not invariably attainable with machine learning or supervised image classification methods. In many instances, it depends on the selection of parameters, the data structure, and the radiometric properties of the objects of classes.

KEYWORDS

Machine learning, Supervised, Unsupervised, Land cover classification

1. INTRODUCTION

Land cover classification is a crucial method for analyzing various land cover types. It plays an essential role in understanding a specific land area's potential uses. Meanwhile, remote sensing (RS) is regarded as a vital tool for managing different types of land cover, as it provides real-time information about the conditions and status of various classes or phenomena [1-2] The image classification of RS datasets is one of the most widely used and efficient techniques for obtaining reliable land cover information [3-4]. This process involves the grouping and labeling of pixel groups within an image based on their spectral and other characteristics, applying specific decision rules [5-6]. Commonly employed techniques include supervised and unsupervised classifications, rule-based approaches, and machine learning methods [7-9].

Machine learning methods have emerged as an effective tool for distinguishing various land cover types. This subfield of artificial intelligence employs algorithms trained on data sets to develop self-learning models that can predict outcomes and classify information with high precision and accuracy [10]. The process involves optimizing model parameters—internal variables—through calculations, ensuring that the model's behavior aligns with the data or experience. As learning progresses, the algorithm continuously updates these parameter values, allowing the model to learn and make predictions or decisions based on data science principles. These algorithms have demonstrated remarkable efficiency in processing a wide range of remote sensing data with varying spectral and spatial properties [11].

Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for classifying all other pixels in the image. The training sites (also known as testing sets or input classes) are selected based on the knowledge of the user. The user also sets the bounds for how similar other pixels must be to group them together. These bounds are often set based on the spectral characteristics of the training area and some other properties. Unsupervised classification involves the grouping of pixels with shared characteristics based on the software's analysis of an image, without input from the user regarding sample classes. The computer employs various techniques to identify related pixels and organizes them into distinct classes. While the user can specify the algorithm the software should utilize and the desired number of output classes [12].

Although various advanced classification algorithms have emerged to classify a variety of remotely sensed datasets, traditional supervised and unsupervised methods can sometimes perform better. Therefore, this study aims to evaluate the performance of machine learning techniques, as well as supervised and unsupervised methods, in discriminating land cover classes in Mongolia. The classification methods used in this research include SVM, Mahalanobis distance, and K-means clustering.

2. STUDY AREA AND DATASETS

As a test site, a north-western part of Lake Khuvsgul, northern Mongolia, has been selected. The Lake Khuvsgul lies sticking into the southern fringe of the Siberian Taiga on the northern frontier of Mongolia, at an altitude of 1645 m above sea level. The lake is the largest freshwater lake in Mongolia containing 70% of Mongolian freshwater sources [13]. Although the selected portion of the Lake Khuvsgul area includes only 3 land cover classes such as forest, soil, and water, there are very high statistical overlaps between the forest and soil classes.

In the present study, the RS datasets used consisted of 10 spectral bands of Sentinel-2A multispectral images acquired on 08 September 2022. Sentinel-2A images have different processing levels. In our study, data with processing level-2A has been used. A natural color image of Sentinel-2A containing some examples of available land cover classes is shown in Figure 1.

RS images often contain a variety of features that require substantial resources to extract. The more features that are analyzed, the more engaging the task becomes. Therefore, selecting the most informative features is a crucial step in the classification of RS images. In our study, for the identification of available land cover classes, the following feature combinations were determined:

1. The blue, green, and near infrared bands (i.e. B2, B3, B8) of the Sentinel-2 data
2. The blue, green, red, near infrared, and short-wave infrared bands (i.e., B2, B3, B4, B8a, B11) of the Sentinel-2 data
3. The original 10 spectral bands (i.e. B2, B3, B4, B5, B6, B7, B8a, B9, B11, and B12) of the Sentinel-2 data

3. CLASSIFICATION METHODS

In this study, we used and compared such classification techniques as a SVM, Mahalanobis distance, and K-means clustering for the discrimination of the available land cover classes in the selected test area.

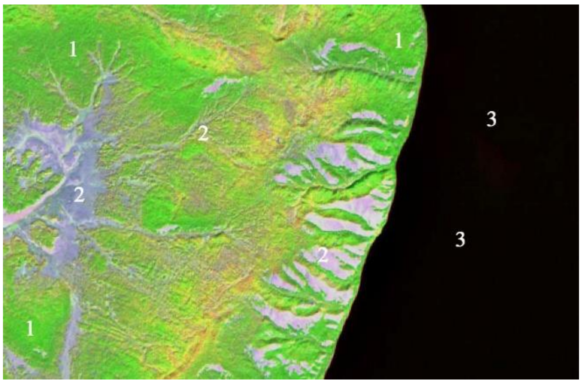

Figure 1. A natural color image of Sentinel-2A
1-forest, 2-soil, 3-water

The SVM algorithm is employed to classify data by transforming the original feature space and constructing an optimal hyperplane in a multidimensional setting. This hyperplane effectively separates data points representing different classes, aiming to maximize the margin between the closest points of these classes [14]. The number of features in the input data determines whether the hyperplane appears as a line or a plane in an N-dimensional space. Due to the existence of multiple hyperplanes that can differentiate classes, the algorithm identifies the best decision boundary by maximizing the margin between data points. In the realm of digital image processing, it can effectively identify necessary support vectors and achieve higher estimation accuracy than other classification methods, even with relatively small training samples [15].

The Mahalanobis distance is a commonly used metric in cluster analysis and classification techniques. It quantifies the distance between a point and a distribution of points while considering the covariance between different variables [16]. In pattern recognition and classification tasks, the Mahalanobis distance helps determine how similar or dissimilar a test point is to a set of training points with known class labels. Unlike many other supervised classification techniques, this direction-sensitive distance classifier assumes that the covariances of all classes are equal. As a result, it operates more quickly, classifying all pixels into the class that has the minimum Mahalanobis distance [17].

K-Means is an unsupervised classification algorithm that begins by calculating initial class means distributed evenly across the data space. It then iteratively clusters pixels into the nearest class using a minimum-distance approach. In each iteration, class means are recalculated, and pixels are reclassified based on these new means. All pixels are assigned to the nearest class, unless a standard deviation or distance threshold is set, in which case some pixels may remain unclassified if they do not meet these specified criteria [18]. This iterative process continues until the number of pixels in each class changes by less than the established pixel change threshold or the maximum number of iterations is reached. The advantages of K-Means include its ease of implementation, scalability to large datasets, guaranteed convergence, and its ability to accommodate clusters of varying shapes and sizes [19].

4. RESULT AND DISCUSSION

Initially, two to three regions of interest (ROIs) were defined to represent the available land cover classes through careful analysis. The separability of the training signatures was first assessed in feature space and then evaluated using the Jeffries-Matusita (JM) distance. This distance calculates the statistical measure of dissimilarity or separability between two data sets based on their probability distributions. Following this investigation, the samples that demonstrated the greatest separability were selected to form the final signatures. The final signatures included 3120 pixels for forest, 1582 pixels for soil, and 295 pixels for water.

For the accuracy assessment of our study, we used overall classification accuracy (OCA). The OCA calculates the total number of correctly classified instances by comparing reference pixels with classified pixels to generate a confusion matrix. This matrix produces an accuracy report that indicates overall accuracy percentages [20].

To ensure accurate ground truth information for the test area, we selected 3 to 5 regions that contained the purest pixels for each available class. This selection was based on the observation that larger classes, such as forest and water, provided more pixels for evaluation. In total, we used 3,462 pixels for the forest, selected from 5 regions; 965 pixels for soil, selected from 4 regions; and 1,591 pixels for water, selected from 3 regions.

In the present study, we employed the SVM classifier utilizing a second-degree polynomial kernel function. This approach captures the similarity of training vectors within a multidimensional feature space based on polynomials of the original variables, enabling the learning of non-linear models. Regarding the Mahalanobis distance, we have thoughtfully chosen a single value for the maximum distance error, which was integrated into the final decision-making process. Additionally, for the K-Means technique, we established a maximum class count of 3 and set the maximum number of iterations at 25.

The final classified images for the first feature combination are displayed in Figure 2a-c. As seen from Figure 2, it is evident that the K-Means technique produced the least favorable outcome, achieving an overall accuracy of only 70.08%. This result starkly reveals considerable statistical overlaps between the forest and soil areas, with a significant portion of the soil class being misclassified and inaccurately represented by pixels belonging to the forest class. Notably, the water class stands out with a strikingly distinct appearance in this classification, highlighting its clear separation from other land cover types. Importantly, these overlaps diminish markedly in the subsequent classification results. In a more promising development, the SVM method, which leverages three spectral bands from the multispectral image, yielded an impressive overall accuracy of 92.72%, positioning it as the most effective classification approach. The Mahalanobis distance classifier followed closely behind, showcasing its strong performance with an overall accuracy of 90.36%. While both the SVM and Mahalanobis distance classifiers produced similar results for the selected land cover classes, the nuanced differences in their statistical overlaps between the forest and soil classes underscore the need for further exploration.

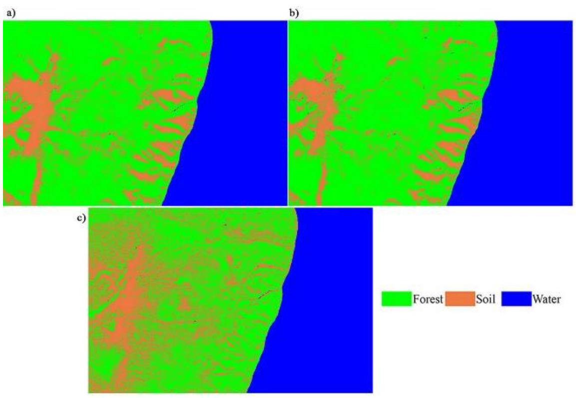

Figure 2. Comparison of classification results using the first feature combination:
(a) the SVM algorithm, (b) the Mahalanobis distance, (c) the K-Means

In the next step, we classified the blue, green, red, near-infrared, and short-wave infrared bands of the Sentinel-2 dataset. The results of these classifications are shown in Figures 3a-c. As illustrated in Figure 3, the five-band combination using the K-Means technique yielded the best result, with a significantly improved classification accuracy of 95.56% compared to the three-band combination. Further analysis revealed that the Mahalanobis distance classifier also performed exceptionally well, as depicted in Figure 3c, achieving a classification accuracy of 95.07%, which is an enhancement over the previous combination. This suggests a reduced statistical overlap between the forest and soil classes. In the same combination, the SVM method, shown in Figure 3a, produced the poorest result compared to the other two techniques. However, both the Mahalanobis distance and SVM classifiers provided similar outcomes for the selected classes, indicating comparable statistical overlaps. Although the SVM method yielded the lowest overall accuracy at 93.33%, it still showed an improvement over the three-band combination. Notably, in all classification outputs, the water class was distinctly separated from the other two land cover classes, highlighting its clear differentiation.

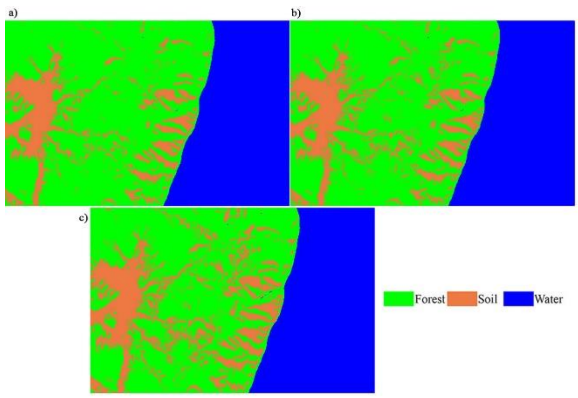

Figure 3. Comparison of classification results using the second feature combination:
(a) the SVM algorithm, (b) the Mahalanobis distance, (c) the K-Means

In the final step of our analysis, we analytically classified the original 10 spectral bands from the Sentinel-2 dataset. The outcomes of these classifications are presented in Figures 4a-c. As depicted in Figure 3, the combination of all ten spectral bands using the K-Means clustering technique again generated the most favorable result, achieving a classification accuracy of 95.83%. This was a slight improvement over the five-band combination, highlighting the enhanced ability of the K-Means method to capture the complexity of the data. Further examination revealed that the Mahalanobis distance classifier once again delivered the second-best performance, as illustrated in Figure 4b, with a classification accuracy of 93.93%. Nonetheless, this accuracy was slightly lower than that achieved with the K-Means approach, indicating its limitation. In contrast, the SVM technique, shown in Figure 3a, generated the least favorable result, with a classification accuracy of 93.14%, underscoring its relative ineffectiveness against the other two methods tested. Interestingly, despite the variations in overall accuracy, both the Mahalanobis distance and SVM classifiers produced comparable outputs for the selected land cover classes. A noteworthy finding across all classification outputs was the distinct separation of the water class from the terrestrial land cover classes, accentuating its clear differentiation and allowing for improved identification and analysis of aquatic environment.

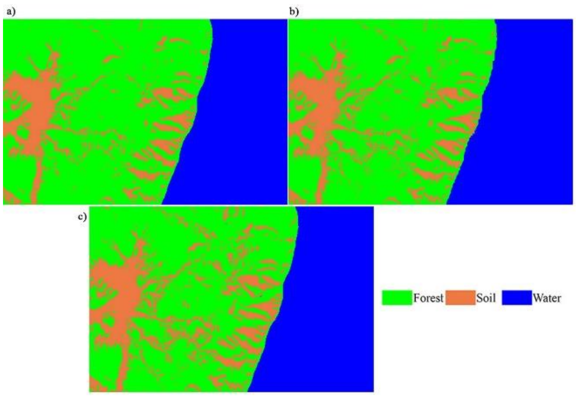

Figure 4. Comparison of classification results using the third feature combination: (a) the SVM algorithm, (b) the Mahalanobis distance, (c) the K-Means

Previous studies have consistently highlighted the advantages of machine learning approaches, particularly the SVM, in classification tasks. For example, Pal and Mather [21] and Mountrakis et al. [22] demonstrated that SVMs often surpass traditional classifiers, especially in high-dimensional feature spaces or when faced with limited training data. Similarly, the Mahalanobis distance classifier has been considered a reliable parametric method for classification when the class covariance structures are clearly defined [23]. However, the findings of this study diverge from the prevailing consensus by revealing that the unsupervised K-means clustering method outperformed both the SVM and Mahalanobis classifiers when five or more spectral bands were employed. This is contrary to the common belief that unsupervised methods generally exhibit lower accuracy due to their reliance on indirect class separation. Nonetheless, research by Franklin et al. [24] has suggested that in homogeneous areas or when spectral separability is pronounced, unsupervised techniques can achieve competitive accuracy.

The performance of K-means in this study highlights the significance of contextual factors—specifically, spectral richness and the nature of land cover heterogeneity. It indicates that under certain conditions, unsupervised methods may not only rival but potentially exceed the performance of more sophisticated classifiers. This aligns with emerging findings in contemporary RS literature that advocate for re-evaluating traditional methods in the context of modern, data-rich environments.

5. CONCLUSION

The aim of this research was to compare the performance of machine learning methods, both supervised and unsupervised, in distinguishing land cover classes in Mongolia. The study utilized data from 10 spectral bands of the Sentinel-2A dataset. To identify the available land cover classes, three different feature combinations and three classifiers—namely SVM, Mahalanobis distance, and K-Means techniques—were applied. In the initial feature combination, which utilized 3 spectral bands, the K-Means technique recorded the lowest overall accuracy of 70.08%. In contrast, the SVM method significantly improved the accuracy to 92.72%. The Mahalanobis distance classifier closely followed, achieving an accuracy of 90.36%. Using a five-band combination, the K-Means technique further enhanced its accuracy to 95.56%, surpassing the results of the three-band combination. The Mahalanobis distance classifier also performed well, reaching an accuracy of 95.07%. Meanwhile, the SVM method lagged behind at an accuracy of 93.33%. In the analysis, which incorporated all ten spectral bands, K-Means again demonstrated its superiority by achieving an accuracy of 95.83%. The Mahalanobis distance classifier attained 93.93%, while the SVM method yielded a lower accuracy of 93.14%. A significant outcome throughout this analysis was the clear distinction of the water class from the terrestrial land cover classes. Overall, the findings suggested that achieving high accuracy is not always possible for machine learning or supervised image classification methods.

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