Remote Sensing Classification Features of Typical Plant Communities in the Semi-arid Region of Eastern Ningxia: Postprint

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Abstract

Taking the Ningxia Habahu National Nature Reserve as the study area, this study investigates the extraction of remote sensing information for typical plant communities at the regional scale, and validates the applicability of using multi-temporal Landsat 8 data for plant community extraction in this region. Based on the Optimal Index Factor, the optimal band combination is determined; simultaneously, combined with the object-oriented classification method, a comparative analysis is conducted on a total of eight classification experiments using single-date imagery and two-date imagery with different band combinations to explore the impact of multi-temporal data on classification accuracy. The results show that: (1) Different segmentation parameter settings have a certain impact on classification accuracy, and the optimal classification effect in the experiments is achieved when the compactness factor and shape factor are 0.7 and 0.1, respectively; (2) Vegetation planted over large areas through human intervention in the study area demonstrates better classification results, while naturally mixed plant communities such as Nitraria tangutorum and Achnatherum splendens are prone to misclassification and confusion; (3) Based on the final classification accuracy, using multi-temporal data for classification can significantly improve classification accuracy, with the overall classification accuracy and Kappa coefficient improved by a maximum of 8.24% and 0.10, respectively, compared with single-temporal data, which can effectively improve the extraction accuracy of vegetation information in the study area.

Full Text

Remote Sensing Classification Characteristics of Typical Plant Communities in the Semi-Arid Areas of Eastern Ningxia

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Abstract

Taking the Habahu National Nature Reserve in Ningxia as the study area, this research investigates the extraction of typical plant community information at the regional scale using remote sensing, verifying the applicability of multi-temporal Landsat 8 data for plant community extraction in this region. Based on the Optimum Index Factor, the optimal band combination was determined. Combined with the object-oriented classification method, eight groups of classification experiments using single-phase and two-phase images with different band combinations were compared and analyzed to explore the influence of multi-temporal data on classification accuracy. The results show that: (1) Different segmentation parameter settings have certain impacts on classification accuracy, with the compactness factor and shape factor achieving the optimal classification effect at 0.7 and 0.1, respectively; (2) Artificially planted vegetation in large areas of the study area shows better classification results, while naturally mixed plant communities such as *Nitraria tangutorum* and *Achnatherum splendens* are prone to misclassification and mixing; (3) According to the final classification accuracy, using multi-temporal data for classification can significantly improve classification accuracy, with overall classification accuracy and Kappa coefficient increasing by a maximum of 8.24% and 0.10 compared with single-phase data, which can effectively improve the extraction accuracy of vegetation information in the study area.

Keywords: object-oriented classification; multi-temporal data; plant community; band combination; classification accuracy; semi-arid areas

Introduction

Plant communities are units of plant populations that develop under specific climate, soil, and topographic conditions, representing a comprehensive indicator of fundamental land attributes that play important roles in environmental restoration and biodiversity enhancement. Particularly in arid and semi-arid regions, vegetation serves a critical function in desertification control. Therefore, accurately obtaining the distribution of plant communities is a prerequisite for further understanding and protection, as well as an important basis for ecological restoration and construction.

Currently, vegetation extraction primarily relies on field surveys and remote sensing technology. Given the temporal and spatial advantages of remote sensing, vegetation classification methods based on remote sensing have been extensively applied to vegetation information extraction and dynamic change monitoring. Common multispectral data and high-resolution multispectral data are widely used, with 20-30 m spatial resolution Landsat imagery being more suitable for medium-scale vegetation extraction. Some scholars have applied object-oriented classification methods to medium-resolution imagery and achieved good results. For instance, Ren Chuanshuai et al. used Spot-6 imagery to monitor mangrove orchards in western Sanya, verifying that object-oriented classification can significantly improve classification accuracy. Douglas used Landsat 8 imagery to study land cover and land use classification in agricultural landscapes at the Poland-Ukraine border. However, object-oriented classification methods for medium-resolution remote sensing imagery have mainly focused on land use/cover, crop, and forest species identification. Multi-source remote sensing data can avoid the defects of single-source data in spectral and spatial resolution, and combining multi-source remote sensing data with multi-features for ground object classification can also improve final classification accuracy. Meanwhile, due to the phenomena of same object with different spectra and different objects with same spectrum, using single-temporal imagery for vegetation information extraction has certain biases. How to use multi-temporal data to improve classification accuracy while avoiding information redundancy deserves further study.

The Habahu National Nature Reserve in Ningxia is located on the western edge of the Ordos Plateau, with low annual precipitation and intense evaporation, complex flora and fauna geographical composition, and typical representation in semi-arid desert steppe areas. This study takes this reserve as the research area, based on multi-source remote sensing data including multi-temporal Landsat 8 imagery and UAV orthophotos, extracts spectral features of plant communities with significant ecological restoration effects, and conducts regional-scale classification research using the object-oriented classification method. The ultimate goal is to obtain regional-scale plant community distribution information to provide theoretical support for ecological protection and sustainable utilization policies in the Habahu National Nature Reserve.

1.1 Study Area Overview

The Habahu National Nature Reserve (hereinafter referred to as the Reserve) is located in the central-northern part of Yanchi County, Ningxia Hui Autonomous Region, with geographical coordinates of 106°53 26 ~107°39 38 E, 37°37 17 ~38°02 04 N, covering an area of 84,000 hm^2. The elevation ranges from 1,200 to 1,622 m, mostly gentle slope terraces. The Reserve belongs to the mid-temperate arid climate zone with typical continental climate characteristics, representing a desert steppe-wetland ecosystem type. The annual average temperature is 7.1°C, annual average precipitation is 285 mm (mainly concentrated in July-September), and annual average evaporation is 2,727.4 mm.

1.2.1 UAV Data

A UAV equipped with a MicaSense RedEdge multispectral camera was used to collect spectral data of typical plant communities in the field survey area of the Reserve on July 31, 2021 (Fig. [Figure 1: see original paper]). The flight altitude was within 120 m, obtaining blue, green, red, red-edge, and near-infrared bands—five narrow spectral bands in total—with ground resolution within 5 cm. The data were resampled to 1 m using the nearest neighbor method in ENVI 5.1 software. Conventional UAV imagery data serve as support for remote sensing image interpretation and classification result validation. Simultaneous UAV flight experiments were conducted on typical plant communities in the same area, with a flight altitude of 120 m. Pix4Dmapper software was used for UAV aerial image processing, including image screening, color equalization, image matching of 同名 points, point cloud calculation, and image mosaicking to generate visible-light orthophotos of the photographed area (Digital Orthophoto Map), with ground resolution within 5 cm.

1.3 Research Methods

The object-oriented classification method considers spectral information while incorporating structural and textural information, enriching the basis for judgment and reducing misclassification and mixing. It is suitable for study areas with complex vegetation resources and intergrown plant communities. This study implements object-oriented classification based on eCognition software, with all images undergoing standard false-color transformation during the classification process.

1.3.1 Band Optimization Method The Optimum Index Factor (OIF) is a commonly used characteristic band extraction method that reflects the information quality of band combinations based on correlation coefficients between bands and standard deviations within bands. Larger values indicate richer information in the bands and less information redundancy between bands. The calculation formula is:

$$OIF = \frac{\sum_{i=1}^{n} S_i}{\sum_{i=1}^{n} \sum_{j=1}^{n} |R_{ij}|}$$

where OIF represents the Optimum Index Factor; S_i is the standard deviation of the i-th band, with larger values indicating richer information in the band; R_{ij} is the correlation coefficient between the i-th and j-th bands, with larger values indicating higher information overlap and greater redundancy between bands; and n is the number of selected bands (generally 3).

1.3.2 Multi-Scale Segmentation Multi-scale segmentation is the principle of first calculating the weights and comprehensive feature values of each band, then calculating the weighted feature values of all bands, and comparing them with the previously set threshold through repeated iterative operations until the weighted value exceeds the threshold, completing the segmentation process. The main factors affecting segmentation results are scale, shape, compactness, and the weights of participating segmentation layers. Homogeneity is a very important indicator in multi-scale segmentation, consisting of two parts: shape factor and compactness. Compactness affects the degree of size difference between the final segmented objects. Under certain scale and shape parameters, smaller compactness results in more fragmented segmentation, while larger shape factor settings result in smaller differences between segmented patches.

1.3.3 Nearest Neighbor Classification Algorithm The nearest neighbor classification algorithm requires determining ground object categories, selecting representative objects from each category as training samples, configuring appropriate feature spaces, and finally completing classification based on the membership values between objects to be classified and each type. Each classification must define samples and feature spaces. In addition to the eight typical plant communities, this study added water bodies and others (construction land, roads, disturbed land, sand land, and bare land in the study area) as classification objects, totaling ten categories. The feature space in this study consists of the mean values of the seven bands of Landsat 8 and vegetation indices calculated from them (Table).

1.3.4 Accuracy Assessment To control the influence of subjective human factors on classification results, the same classification sample library was used during classification, and accuracy verification utilized the same pixel-based confusion matrix to improve the credibility of accuracy evaluation results. The specific experimental scheme is shown in Table .

2.1 Typical Plant Community Selection and Spectral Feature Extraction

Given the 30 m spatial resolution of Landsat 8 satellite remote sensing imagery, plant community selection should ensure not only concentrated and continuous distribution with obvious dominant species but also that community distribution area exceeds the 30 m scale. Based on vegetation growth status in the study area and field survey results, eight typical plant communities were identified (Table). A total of 40 sampling points were selected across the plant communities. Based on the UAV orthophoto images (Fig. [Figure 2: see original paper]), the sampling area was appropriately expanded according to texture information in ArcGIS 10.7 software. Landsat 8 image spectral values were extracted and arithmetically averaged to create spectral curves.

The results show that on February 21, 2021, the plant communities formed a relatively stable reflectance ranking among the seven bands, with minor mutations in each band. However, the stable differences between different communities in each band represent a comprehensive response of plant community spectra and soil background spectral characteristics during the non-growing season. This information differs significantly from spectral characteristics during vigorous growth periods and enriches spectral features in the temporal dimension. On July 31, 2021, the plant communities formed stable reflectance in the first four bands, but the reflectance gap gradually widened in the fifth band, followed by a sudden change in the sixth band where reflectance rose sharply, forming a new reflectance ranking. This is due to the "red edge" phenomenon formed by the internal structure of vegetation leaves in the red and near-infrared bands. The seventh band belongs to atmospheric water strong absorption bands, where similar reflectance rankings were formed again.

2.2 Optimal Band Selection

Based on the OIF calculation formula, the correlation coefficients between bands and standard deviations of each band were calculated. The OIF values of 35 band combinations were ranked as shown in Table . The final optimal band combination must be determined in combination with the spectral characteristics of each plant community. From the extracted plant community spectral curves (Figs. [Figure 3: see original paper] and [Figure 4: see original paper]), significant differences are observed in the first four bands (coastal, blue, green, red), followed by the original ranking being broken in the fifth band (NIR), with spectral reflectance differences significantly enhanced. Combined with the correlation coefficient matrix (Table), the correlation coefficient between bands 5 and 6 is the smallest, initially determining that the optimal band requires band 5. Meanwhile, bands 5, 6, and 7 have relatively large combined standard deviations and small correlation coefficients, indicating rich information content and low information redundancy between bands. Therefore, the final optimal band combination was determined as 5-6-7 (NIR-SWIR1-SWIR2).

2.3 Segmentation Parameter Selection

2.3.1 Segmentation Scale Selection In the experiment, four segmentation scales (30, 40, 50, 60) were tested (Fig. [Figure 5: see original paper]). At a segmentation scale of 30, over-segmentation occurred with overly fragmented results. At a scale of 60, plant community details were insufficiently segmented with overly coarse results. At scales of 40 and 50, the results were more reasonable, capable of more completely reflecting ground object features. Considering the complexity of vegetation components in the study area, a scale of 40 was selected as the optimal segmentation scale.

2.3.2 Homogeneity Factor Determination From the visual interpretation effect, controlling compactness and shape factors separately, the experimental results are shown in Fig. [Figure 6: see original paper]. With the segmentation scale fixed at 40 and the shape factor at 0.1, compactness parameters of 0.3, 0.5, 0.7, and 0.9 were compared. As the shape factor increases, the boundaries of segmented objects tend to become smoother, but the segmented patches also gradually enlarge. Considering the complex vegetation components in the study area, the experimental group with more detailed segmentation results was selected, with shape factor = 0.1. Under conditions of segmentation scale = 40 and shape factor = 0.1, compactness parameters were set to 0.3, 0.5, 0.7, and 0.9 for comparison. As compactness increases, segmentation patches are further refined. Considering the intergrowth of *Nitraria tangutorum* and *Achnatherum splendens* communities, the experimental group with more detailed segmentation results was again selected, with compactness = 0.5.

To further study the influence of compactness and shape factors on segmentation results, classification accuracy was evaluated using Landsat 8 bands 5-6-7 with scale parameter = 40. Controlling shape factor = 0.1, compactness parameters of 0.1-1 were tested at intervals of 0.1. As shown in Fig. [Figure 7: see original paper], classification accuracy first decreases and then increases with increasing compactness. Within the 0.1-0.7 range, overall accuracy is relatively high but shows a downward trend. Within the 0.7-0.9 range, there is a sudden change, with classification accuracy decreasing significantly. The maximum accuracy is achieved at compactness = 0.5. Controlling compactness = 0.5, shape factors of 0.1-0.9 were tested at intervals of 0.1. As shown in Fig. [Figure 8: see original paper], overall accuracy does not fluctuate significantly within the 0.1-0.7 range, but there is a mutation within the 0.7-0.9 range, where classification accuracy decreases substantially. The maximum is reached when shape factor = 0.1. Therefore, the final determined parameters are compactness = 0.5 and shape factor = 0.1.

2.4 Accuracy Analysis and Evaluation

Using two-phase Landsat 8 multispectral remote sensing data and calculated index layers, the vegetation growing season (July 31) and non-growing season (February 21) image bands were combined in four ways and used with the object-oriented classification method, totaling eight groups of classification experiments (Table). The results were mapped (Figs. [Figure 9: see original paper] and [Figure 10: see original paper]).

The highest overall classification accuracy was achieved by Group E (two-phase 5-6-7 band combination), with overall accuracy and Kappa coefficient of 83.98% and 0.78, respectively. From the confusion matrix (Table), producer accuracies for single plant communities such as poplar, tamarisk, and *Artemisia desertorum* are relatively high, at 90.32%, 92.10%, and 87.50%, respectively. *Pinus sylvestris* var. *mongolica* and *Caragana microphylla* communities have lower producer accuracies of 46.88% and 66.67%, respectively. From the user accuracy perspective, except for *Achnatherum splendens* and *Nitraria tangutorum* communities at 60.00%, all other plant communities have user accuracies greater than 70%, indicating less misclassification. The *Achnatherum splendens* community contains mixed classifications of *Nitraria tangutorum*, *Pinus sylvestris* var. *mongolica*, and *Caragana microphylla*, accounting for 12.90%, 25.81%, and 9.68% of the total *Achnatherum splendens* samples, respectively. There is also mutual misclassification between *Nitraria tangutorum* and tamarisk and *Pinus sylvestris* var. *mongolica*. This analysis indicates that using two-phase data can meet the classification requirements for plant communities in the study area and achieve relatively high accuracy, demonstrating that the object-oriented classification method effectively improves classification accuracy by comprehensively utilizing spectral, geometric, and other features of classification objects.

Discussion

This study achieved high classification accuracy using multi-temporal Landsat 8 data, meeting research requirements and providing methodological references for large-scale plant community extraction in the reserve. However, some issues remain. The user accuracy of *Achnatherum splendens* and *Nitraria tangutorum* is relatively low. After analysis, this is determined to be due to the influence of background information on community boundaries and plant spectral features when vegetation coverage of some naturally distributed plant communities is low. In contrast, vegetation such as *Caragana microphylla* and *Salix cheilophila*, which have been extensively planted in the study area in recent years, shows higher classification accuracy, related to artificial planting methods that facilitate clear boundaries, ideal habitats, and good vegetation coverage. This study used image multi-scale segmentation combined with visual judgment to delineate plant community ranges, requiring high-resolution UAV imagery and rich field survey experience as support. Future research should further summarize multi-scale segmentation parameters applicable to the study area to reduce dependence on subjective experience. Additionally, this study only compared the nearest neighbor classification method based on pixel spectral features and object-oriented methods, while how to use combinations of multiple classifiers to improve classification accuracy deserves further in-depth research.

Due to relatively insufficient texture information in medium-resolution imagery, blurred boundaries between some plant communities, and the "same object with different spectra" phenomenon caused by intergrown plant communities and inconsistent vegetation growth states, some mixing and misclassification occurs. How to improve classification accuracy for easily confused plant communities and increase comprehensive multi-dimensional remote sensing information for typical plant community identification will be the focus of future research.

Conclusions

Based on the spectral characteristics of plant communities in growing and non-growing seasons, combined with two-phase imagery analysis, this study achieved classification of typical plant communities in the study area using multi-temporal imagery and object-oriented methods, improving classification accuracy to some extent. The conclusions are as follows:

1) Typical plant communities in the study area have different spectral characteristics. Overall classification accuracy varies with compactness and shape factor parameters. When shape factors are 0.1 and 0.3, the classification accuracy difference reaches a maximum of about 5%. With compactness parameter at 0.5, the difference reaches a maximum. The optimal segmentation parameters are compactness = 0.5 and shape factor = 0.1.

2) From the classification results of the eight experimental groups, the overall classification accuracy using two-phase image data is higher than that using single-phase image data. The maximum overall classification accuracy and Kappa coefficient are 83.98% and 0.78, respectively, which are 8.24% and 0.10 higher than the optimal three-band combination (Group D), indicating that using only single-phase imagery results in insufficient spectral differences between some plant communities and poor classification effects.

3) In terms of user accuracy of each classification object, poplar, tamarisk, *Artemisia desertorum*, and *Caragana microphylla* show high spectral distinctiveness and correspondingly high user accuracy.

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Note: Figure translations are in progress. See original paper for figures.