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Using Unmanned Aerial Vehicle multispectral data for monitoring outcomes of ecological restoration in mining areas

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Abstract

The effective and efficient monitoring of revegetation outcomes is a key component of ecosystem restoration. Monitoring often involves labour intensive manual methods which can be difficult to deploy when sites are inaccessible or involve large areas of revegetation. This study aimed to identify plant species and quantify α-diversity index on a sub-meter scale at Manlailiang Mine Site in Northwestern China using unmanned aerial vehicles (UAVs) as a means to semi-automate large-scale vegetation monitoring. UAVs equipped with multispectral sensors were combined with three industry-standard supervised classification algorithms (support vector machine (SVM), maximum likelihood, and artificial neural network) to classify plant species. Spectral vegetation indices (NDVI, DVI, VDVI, SAVI, MSAVI, EXG - EXR) were used to assess vegetation diversity obtained from on-ground survey plot data (Margalef, Pielou, Simpson, Shannon indices). Our results showed that SVM outperformed other algorithms in species identification accuracy (overall accuracy 84%). Significant relationships were observed between vegetation indices and diversity indices, with DVI performing significantly better than many more commonly used indices such as NDVI. The findings highlight the potential of combining UAV multispectral data, spectral vegetation indices and ground surveys for effective and efficient fine-scale monitoring of vegetation diversity in the ecological restoration of mining areas. This has significant practical benefits for improving adaptive management of restoration through improved monitoring tools.

Using Unmanned Aerial Vehicle multispectral data for monitoring outcomes of ecological restoration in mining areas

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Abstract:

The effective and efficient monitoring of revegetation outcomes is a key component of ecosystem restoration. Monitoring often involves labour intensive manual methods which can be difficult to deploy when sites are inaccessible or involve large areas of revegetation. This study aimed to identify plant species and quantify α-diversity index on a sub-meter scale at Manlailiang Mine Site in Northwestern China using unmanned aerial vehicles (UAVs) as a means to semi-automate large-scale vegetation monitoring. UAVs equipped with multispectral sensors were combined with three industry-standard supervised classification algorithms (support vector machine (SVM), maximum likelihood, and artificial neural network) to classify plant species. Spectral vegetation indices (NDVI, DVI, VDVI, SAVI, MSAVI, EXG - EXR) were used to assess vegetation diversity obtained from on-ground survey plot data (Margalef, Pielou, Simpson, Shannon indices). Our results showed that SVM outperformed other algorithms in species identification accuracy (overall accuracy 84%). Significant relationships were observed between vegetation indices and diversity indices, with DVI performing significantly better than many more commonly used indices such as NDVI. The findings highlight the potential of combining UAV multispectral data, spectral vegetation indices and ground surveys for effective and efficient fine-scale monitoring of vegetation diversity in the ecological restoration of mining areas. This has significant practical benefits for improving adaptive management of restoration through improved monitoring tools.

Keywords

ecological restoration, revegetation, mine site restoration, α-diversity, monitoring, mine regulation

1 Introduction

Plant species diversity is a fundamental goal for ecological restoration particularly in mining areas where functional and often biodiverse ecosystems need to be reinstated (Brancalion and Holl, 2020; McKenna et al., 2020; Han et al., 2021; Chen et al., 2022). Ensuring complete species mixes are reinstated in restoration programs can improve ecosystem function and stability, particularly for alleviating impacts of extreme or unexpected environmental events (Naeem et al., 1994; Gaston, 2000; Isbell et al., 2015; Hauser et al., 2021; Fremout et al., 2022). The UN Decade of Ecosystem Restoration highlights the importance of re-vegetating with complex species mixes (Zhang et al., 2021), while various ecological restoration standards (Gann et al. 2019, Young et al. 2022) emphasise the importance of matching native reference sites with species mixes to ensure restored areas are resilient and functional (Yang et al., 2022; Young et al., 2022). Despite major investments by governments, mining companies, and land managers to restore ecosystems after mining, restoration for many mines particularly those in native ecosystems remains difficult and complex to achieve (Menz et al., 2013). Importantly, once resource extraction has been completed many companies are not willing to invest additional time, resources, and funding to monitor and evaluate the effectiveness of restoration practices, severely hindering the capacity to keep projects on track (Galatowitsch and Bohnen, 2020). An observed phenomenon is that restoration projects tend to prioritize short-term vegetation cover over long-term biodiversity protection (Hoffmann, 2022), ultimately leading to their failure (Chen et al., 2022). Thus, accurate and efficient vegetation diversity monitoring is crucial for tracking the success of restoration projects and guiding adaptive management strategies (Hoffmann, 2022).

Traditional vegetation survey approaches rely primarily on manual ground surveys at plot level to obtain plant species diversity and abundance and/or structural data but these are often costly, time-consuming, and limited in their ability to monitor large areas (Anderson, 2018; Reddy, 2021). Satellite imagery, on the other hand, has proven to be a valuable tool for automated or semi-automated and repeatable vegetation

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mapping across a range of spatial scales, spanning from regional to community-level, and from low to high spatial resolutions (Li et al., 2021; Villoslada et al., 2020; Randin et al., 2020). However, mining areas are often subject to intense disturbance (Hou et al., 2021; Jiang et al., 2022), resulting in relatively small spatial extent confounded by the often dense regeneration of uniformly aged plants in mine restoration that make it difficult to accurately differentiate taxa when deploying high altitude satellite approaches. In particular, the optical detection of α diversity, which is the foundational biological information in any restoration program (Rocchini, 2007).

To meet the requirements for mine site restoration where high temporal and spatial resolution and site-based data integration are necessary (Lawley et al., 2016), the more nuanced and higher resolution capacity from drone-based analyses may provide useful capacity (Miller et al., 2017; de Almeida et al., 2020). Unmanned Aerial Vehicles (UAVs) are an increasingly common platform for remote sensing data acquisition (Johansen et al., 2019). UAVs enable low-cost, rapid acquisition of high-resolution data at a centimeter scale (Lu and He, 2017; Ren et al., 2019; Alvarez-Vanhard et al., 2020; Belmonte et al., 2020), and can coincide with the timing of site-based assessments (Lawley et al., 2016), making them a convenient tool to aid in vegetation surveys in mining areas.

The applications of UAVs in vegetation assessments in mining areas are wide-ranging, including monitoring vegetation growth conditions such as soil temperature (Ruan et al., 2022); mapping vegetation communities, vegetation structure and height (Banerjee and Raval, 2022; Tang et al., 2022); and assessing biomass (Ren et al., 2022). Multispectral sensors can be used to monitor ecological indicators such as vegetation coverage, aboveground biomass, and tree crown coverage (Villoslada et al., 2020; Fernandez-Guisuraga et al., 2022), and can provide an alternative to high-cost airborne hyperspectral and LiDAR approaches. However, few studies have used spectral information provided by UAV remote sensing integrated with site-based data to identify plant species and provide estimates of diversity.

Studies estimating plant diversity using remote sensing can typically be divided into two categories: direct identification of plant species and their distribution through visual interpretation or image classification algorithms, and indirect methods that establish a relationship between diversity and spectral data, or derive species distribution through habitat mapping (Rocchini, 2007; Madonsela et al., 2017; Wang and Gamon, 2019; Villoslada et al., 2020; Zhu et al., 2022). Many studies use vegetation indices such as NDVI estimate species diversity indirectly, although they do not discriminate well between vegetation communities (Gillespie, 2005; Madonsela et al., 2018; Kacic and Kuenzer, 2022; Tian and Fu, 2022). However, less attention has been given to the sensitivity of vegetation indices to species distributional patterns through visual interpretation or image classification algorithms (Lu and He, 2017; Reddy, 2021).

In this study, we combine on-ground vegetation surveys with UAV multispectral data to map vegetation diversity in mining areas in Northwestern China on a sub-meter scale over tens of hectares and develop classification algorithms to identify plant communities The restoration biome is characterized by the co-existence of trees, shrubs and herbaceous plants with high floral diversity compared to the surrounding area, making fine-scale monitoring necessary to analyze the spatial configuration and diversity distribution of vegetation communities. Our objectives are to: (i) compare the performance of three industry-standard supervised classification methods in identifying plant species and mapping their distributions based on reflectance values, (ii) estimate α-diversity at scales determined by the species-area curve to assess the ability of UAV data, and vegetation indices calculated from this data, to qualitatively and quantitatively map alpha floral diversity. This gives restoration practitioners a robust method to significantly improve the spatial detail and coverage of floral diversity mapping for effective monitoring of restoration projects using UAV-based inventory.

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2 Methodology

2.1 Study Area and Identification of Dominant Vegetation

The study was conducted at the Manlailiang mine site, covering 19.2 km^2 (Figure 1; 39°26'37"-39deg29'55"N, 110deg10'11"-110deg14'02"E), in the Ordos Plateau, Inner Mongolia, Northwestern China. The climate is classified as a dry arid climate common in middle latitude deserts (Koppen climate classification BWk) (Beck et al., 2018). The average precipitation ranges from 250mm to 450mm, while the average evaporation exceeds 1000mm, resulting in a severe excess of evaporation over precipitation (Liu et al., 2020). The predominant soil type is Aenoslos, lacking in fertility with low water-retention capabilities (Liu et al., 2020). Underground coal mining activities took place in 2011 and resulted in fissure and subsidence damage. Small fissures can be self-filled by the movement of wind-blown sandy soil. For areas with large fissures or severe subsidence, crack filling, terrain reclamation and replanting measures were implemented to ensure vegetation growth.

Figure 1 *Study area.*

Prior to the commencement of underground mining, the study area was characterized by a diverse distribution of species and some grazing vegetation communities, consisting mostly of sandy plant communities with perennials and shrubs (Liu et al., 2020; Zhang et al., 2022). The dominant trees were poplar, and the dominant shrubs were Salix*cheilophila* , *Artemisia desertorum* , and *Caragana korshinskii* ; the dominant herbaceous included *Stipa capillat., Bothriochloa ischaemum* and *Setaria viridis* . A total of six dominant vegetation species and bare land were selected for this study, including Poplar, Artemisia, Salix, Caragana, Herb, Corn and Bare ground. Grass was not specifically classified since it occurred under tree canopies and shrubs or was very sparsely distributed on bare land, making it challenging for UAVs to detect or identify specific grass species. Therefore, all types of grass were classified as 'Herb' without detailed evaluation.

2.2 UAV Surveying

A DJI P4-Multispectral UAV equipped with six 1/12.9 inch CMOS image sensors collected spectral data in five bands (blue, green, red, red edge, and near-infrared). The data collection occurred during the peak growth period of vegetation in the Ordos region, from 10:00-14:00 on September 10, 2020. Data were acquired during three separate flights covering a flight area of 38.57ha. Twelve ground control points were used to ensure accurate geopositioning of the data. Standard reference whiteboard correction with a reflectance value of 50% was performed before each flight to avoid overexposure or underexposure due to cloud changes. Flight planning included capturing photos with a 75% forward and side overlap ratio, evenly spaced intervals, a flight height of 120m, a pixel resolution of 6.4cm, and a speed of 9.8m/s. Pre-processing, including image stitching and radiometric correction, was performed by Agisoft PhotoScan (Figure 2).

Figure 2 *Study workflow.*

2.3 Vegetation Surveys

On the same day as the drone flight, a field survey was conducted to provide ground validation of the UAV data and subsequent data processing and classification. In order to maintain the uniformity of species composition, community structure, and habitat, transects were established using stratified sampling. The survey design consisted of three transects, selected based on the characteristics of the underground coal mining faces. Each transect exhibited distinct key features and demonstrated low spatial heterogeneity. Within transects, ten plots were established, comprising four randomly assigned subplots: tree (30m x 30m), shrub (10m x 10m), and herb (1m x 1m) plots including replicates (Figure 3). Vegetation species composition was then identified, and number of individuals, height, and coverage was recorded. Geomorphological features and vegetation communities were located and photographed to aid in identification and validation of the UAV-generated data.

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Figure 3 *Location of vegetation plots.*

2.4 Data Processing

2.4.1 Image Interpretation

Standard false-color images are useful to highlight vegetation features as these are sometimes better suited for identifying certain vegetation than true-color images. To obtain more accurate visual interpretation results, we conducted this study based on standard false-color and true-color images, and the characteristics of vegetation morphology and distribution (Figure 4). We visually interpreted orthophoto images from vegetation plots and selected over 100 training samples for each plant species. Three pixel-based supervised classifiers (Support Vector Machine, Maximum Likelihood, and Artificial Neural Network) in ENVI were used to identify the main vegetation species. Classification results were verified, modified, and interpreted, and their accuracy was validated using synchronous field data. Two accuracy indices were selected: overall accuracy and Kappa coefficient.

Figure 4 *Typical vegetation in the study area .*

2.4.2 Diversity Assessment

Alpha-diversity is commonly used to assess species richness and relative dominance within a target community (Rocchini et al., 2016). Alpha-diversity encompasses different aspects, including species richness, evenness, and diversity (Peet, 1974). Species richness measures the abundance of species in a community, often quantified using the Margalef index (Clifford and Stephenson, 1975). Evenness quantifies the distribution of species within a community, often assessed by the Pielou index (Pielou, 1966); Diversity reflects the overall species richness and evenness and can be evaluated by Simpson's index and Shannon-Wiener index (Simpson, 1948; Shannon, 1949). Grids ranging from 1 x 1m to 100 x 100m were generated using ArcGIS as research units, and vegetation diversity indices were calculated for each grid.

Moran's I analysis was used to explore spatial correlation and clustering patterns of plant diversity (Lozada & Bertin, 2022). Global Moran's I analysis, drawing upon geostatistical theory, is employed to assess the overall spatial clustering of plant diversity (Moran, 1950). Local Moran's I analysis was applied to identify specific local clusters, thereby supplementing the limitations of global spatial autocorrelation in delineating precise clustering regions.

2.4.3 Spectral Vegetation Index

Considering the influence of soil reflectance on diversity assessment within arid and semi-arid regions, the following vegetation indices were selected (Kacic & Kuenzer, 2022): *Normalized Difference Vegetation Index* (NDVI) (Tucker, 1979), *Difference Vegetation Index* (DVI) (Tucker, 1979), *Visible-Band Difference Vegetation Index* (VDVI) (Wang et al., 2015), S*oil Adjusted Vegetation Index*(SAVI) (Huete, 1988), *Modified Soil Adjusted Vegetation Index*(MSAVI) (Qi et al., 1994), and *Excess Green - Excess Red* (EXG - EXR) (Meyer and Neto, 2008). Subsequently, correlation and regression analyses were conducted using the R4.3.0 software to explore the relationship between these vegetation indices and diversity indices.

3 Results

3.1 Vegetation Classification

3.1.1 Classification Accuracy Assessment and Comparisons

All methods achieved an overall accuracy of at least 79% and Kappa coefficient above 0.74, indicating high repeatability and accuracy (Figure 5). Among three methods, SVM demonstrated superior performance,

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exhibiting the highest overall accuracy of 84.0% and Kappa coefficient of at least 0.81. This represents a 5% and 10% higher accuracy compared to the other algorithms, respectively. The confusion matrix of SVM classification can be found in Table 1. It reveals that Caragana, Poplar, and Grass have a high classification accuracy of more than 89%. The classification accuracy of Salix and Artemisia is relatively low, at 71.43% and 72.92% respectively; while Corn is the lowest, at 68.54%.

Figure 5 *Vegetation species mapping and accuracy validation of three supervised classifications.*

Table 1 *The confusion matrix of SVM classification results.*

The three classification methods demonstrated variability in their results across different tree species (Figure 5). Two common issues were identified (Figure 6): commission and omission, and patch fragmentation. Commission and omission were mainly observed in Artemisia, Salix, and Corn communities. UAV images with high spectral resolution facilitated the identification of tree crown shadows, affecting spectral heterogeneity and leading to misclassification of shadows as Artemisia. Meanwhile, the spectral similarity between Artemisia and Salix resulted in increased misclassification. Within the same vegetation environment, variations in age, growth conditions, sizes, and shapes of plant species contributed to significant within-species variability. Additionally, image errors such as irregular changes in intensity density caused by stitching might cause commission and omission, which are unavoidable. The fragmentation of patches was caused by two factors: high spatial resolution, enabling clear identification of gaps between tree and shrub branches, and sparsely distributed grass, resulting in many small fragmented patches that hindered plant spatial structure. Large spectral variation within the same type introduces uncertainty during computer processing, leading to 'speckle' noise. To address these, post-classification analyses (clump analysis and majority/minority analysis) were conducted to refine the results and serve as the basis for calculating plant diversity.

Figure 6 *Main misclassified areas in detail of three supervised methods.*

3.1.2 Distribution of Vegetation Species

Vegetation distribution varies greatly across different regions. Poplar and Caragana are predominantly found in the east, while Poplar and Artemisia are abundant in the central, and Artemisia and Salix are mostly present in the west. Poplar was the primary tree species and formed a vertical community structure of trees-shrubs-herbs. Shrubs like Salix, Artemisia, and Caragana had a patchy distribution, and some Salix and Caragana were planted in rows, whereas Artemisia tended to exhibit a clustered distribution. The clustering of the same species is due to their common habitat requirements, which creates a competitive advantage for the group as a whole, forming a suitable growth environment (Amarasekare, 2003). This may enhance resilience against adverse conditions, species invasion, facilitates resource competition and promotes growth.

Shrubs were the most widely distributed vegetation class, covering 42.5% of the area, followed by Grass and Bare classes (Figure 5-c). Grasslands are common in semi-arid regions, but in the study area, the vegetation is predominantly composed of shrubs, which can be considered a form of shrub-encroached grasslands. However, the ecological succession dynamics and vegetation patterns resulting from shrubification have been extensively discussed, with ongoing debates regarding the stability of this new ecological state and its potential implications for ecosystem functioning and biodiversity conservation (Suding et al., 2004; Pierce et al., 2019; Ding and Eldridge, 2023).

3.2 Vegetation Diversity

3.2.1 Species Accumulation Curves

As the area of a plot increases, there is typically a greater number of species present in the SVM-classified UAV data. We designated the study area into sampling plots of varying scales by ArcGIS and quantified the average species count within each plot area., ultimately creating a species-area curve (Figure 7). The curve exhibits a clear inflection point at the 10m x 10m scale, covering around 65% of the surveyed species. This corresponds to the standard plot size for vegetation surveys. The 30m x 30m scale covers at least 95% of

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the total number of species, meeting the criteria for "minimum area for optimal communities" (Barbour et al., 1980). Additionally, a 30m x 30m plot size is typically used for local vegetation surveys in the semi-arid region of Inner Mongolia, where species numbers are relatively low. Therefore, vegetation diversity was analyzed at 10m x 10m and 30m x 30m scales.

Figure 7 *Species accumulation curves of study site.*

3.2.2 Diversity Distribution at Two Scales

Vegetation diversity is relatively low over the study area, with similar diversity at both scales. The 10m x 10m scale provides more detailed and accurate information on vegetation diversity compared to the 30m x 30m scale (Table 2 and Figure 8). At the 10m scale, the Margalef index indicates a moderate level of species richness, with a mean of 0.760; the Pielou index indicates uneven species distribution, with a mean of 0.295; the Simpson index is more sensitive to the enrichment of species, with a mean of 0.210, indicating a relatively low diversity; the Shannon-Wiener index is most closely related to species richness, with a mean of 0.395.

Table 2 *The mean of each diversity index at two scales.*

Figure 8 *Vegetation diversity indices at two scales: Margalef, Pielou, Simpson and Shannon-Wiener indices.*

The spatial distribution of diversity indices shows a gradual decrease from east to west (Figure 8), influenced by species composition. The eastern region with mixed shrub-grassland has high diversity values, the middle region dominated by trees and shrubs has moderate values, and the western region with shrubs like Artemisia and Salix has low values. Salix possibly has a strong ability to occupy resources, which suppresses the growth of other species. Additionally, its large canopy limits the amount of sunlight reaching vegetation underneath its branches and leaves, resulting in little nearby vegetation (Alvarez et al., 2011; Pierce et al., 2019).

3.2.3 Spatial Autocorrelation Analysis

Spatial autocorrelation analysis was conducted to examine the distribution of vegetation diversity and to determine the presence of clustering. The analysis showed that global Moran's I index for each diversity index was greater than 0, indicating clustering. Shannon index had the highest global Moran's I value among all indices. For example, at two scales, the Moran scatter plots were mainly distributed in the first and third quadrants with global Moran's I indices of 0.469 and 0.463, respectively (Figure 9). Both were statistically significant at the significance level of α=0.05 ($z>1.96$), indicating strong positive spatial autocorrelation and significant spatial clustering rather than random distribution in space. High-high clustering was mainly located in the east of the study area, corresponding to areas of high diversity. In contrast, low-low clustering was mainly located in the west, corresponding to the low-diversity region. High-low and low-high clustering were sporadically distributed throughout the study area. These results demonstrate the spatial distribution characteristics of clustering and differentiation using the Shannon index.

Figure 9 *The Moran scatter plot and spatial autocorrelation clustering map of Shannon-Wiener index.*

3.2.4 The Correlation between Vegetation Indices and Vegetation Diversity

Significant correlations between vegetation and diversity indices were observed at both the 10m $\times$ 10m and 30m $\times$ 30m scales (Figure 10), indicating the possibility of establishing diversity assessment models. At the 10m scale, all six vegetation indices, except the Margalef index with no correlation to NDVI and SAVI, exhibited significant relationships with the four diversity indices. Notably, the correlation coefficients between Pielou, Simpson, Shannon, and DVI, as well as MSAVI, consistently exceeded 0.54 (Table 3). However, at the 30m scale, not all correlations observed at the smaller scale were present. NDVI and MSAVI showed weak or no correlation with the four diversity indices, while Pielou, Simpson, and Shannon exhibited significant positive correlations with the remaining vegetation indices. Overall, whether at the 10m $\times$ 10m or 30m $\times$ 30m scale, DVI showed higher correlation coefficients with Shannon, with values of 0.617 (R^2=0.38, $P<0.01$)

and 0.725 (R^2=0.53, P<0.01), respectively. The diversity assessment model using DVI as the independent variable and Shannon as the dependent variable can be represented as: y=1.667x+0.8364 (10m × 10m) and y=2.3452x+1.0473 (30m×30m), explaining 38% and 53% of the variation, respectively.

Figure 10 *The Correlation between diversity indices (Margalef, Pielou, Simpson and Shannon) and vegetation indices (DVI, MSAVI, NDVI, SAVI, VDVI and EXG-EXR) at Two Scales.*

Table 3 *Pearson correlation analysis between diversity and vegetation index at two scales.*

4 Discussion

4.1 Feasibility of Vegetation Species Identification

The comparative accuracy of species identification algorithms by remote sensing at different scaled has not been extensively studied (Camarretta et al., 2020). This study utilized pixel-based supervised classification to identify plant species by training and validating machine learning algorithms. SVM outperformed maximum likelihood and neural network classifiers in fragmented land plots with mixed vegetation types, exhibiting higher accuracy with limited training samples and minimal Hughes phenomenon. However, pixel-based supervised classification may not fully utilize the textural and structural information capability of remote sensing imagery, leading to "salt and pepper" and "spectral confusion" phenomena, particularly for species with similar spectral characteristics. Future studies may introduce texture features and spatial information (Camarretta et al., 2020), such as LiDAR and digital elevation models, to address these limitations (Shokirov et al., 2023).

Monitoring and evaluation are crucial steps in restoration projects, emphasizing the implementation of practical indicators instead of broadly defined and often ambiguous monitoring standards (Australian Government, 2016; Nilsson et al., 2016; Young et al., 2022). The transition from conceptual ideas to on-ground implementation aims at cost-effective and successful restoration (Evju et al., 2020). This study highlights the benefits of low-altitude UAV multispectral data for cost-effective, easy-to-use, and high-efficiency ecological monitoring at a fine scale, thereby improving the ease and accuracy of monitoring efforts.

Firstly, *the accuracy of low-altitude UAV imagery surpasses that of satellite remote-sensing data* (Johansen et al., 2019). Satellite remote sensing covers a wide spatial extent and diverse landscape types, making it difficult to capture detailed vegetation information (Peng et al., 2021), leading to less precise classification. This is especially true in arid and semi-arid areas where sparse vegetation, a mixture of herbaceous shrubs, and different soil reflectance values complicate accurate vegetation monitoring (Rossi et al., 2022).

Secondly, *UAV multispectral data is more cost-effective than hyperspectral sensors and LiDAR for many applications* (de Almeida et al., 2021; Haneda et al., 2023). Hyperspectral data offers a multitude of spectral bands that enhance diversity detection potential; however, this might result in a decrease in classification accuracy in high spectral dimensions (Gholizadeh et al., 2018). Despite its advantages in characterizing vegetation vertical structure (Fernandez-Guisuraga et al., 2022), the widespread application of LiDAR is significantly limited due to its high expenses. Therefore, practitioners need to weigh both the economic costs of LiDAR and the time costs associated with hyperspectral data analysis. In light of these considerations, integrating UAV multispectral data emerges as the optimal approach for monitoring ecological restoration in mining areas. The cost-effectiveness of UAV multispectral data, compared to hyperspectral sensors and LiDAR, makes it a favorable choice for various applications

The present study has some limitations regarding species classification, which may be improved by combining deep learning and spectral features to increase accuracy and efficiency (Saadeldin et al., 2022) such as the integration of vegetation height and canopy extraction and species classification. Further in-depth research could also explore the effects of lower flight altitudes (e.g. 10-50m) and adjusted flight attitudes (e.g. oblique photogrammetry) for more accurate monitoring of low-growing herbaceous or recently emerged seedlings.

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4.2 Feasibility of UAV-based Vegetation Diversity Monitoring

Field measurements are essential for validating the accuracy of results. Figure 11 shows the relative importance values of vegetation species obtained through field surveys. Poplar, Artemisia, and Salix were ranked as the top three species by importance value, consistent with results from UAV imagery. Poplar dominated the tree layer, while Artemisia dominated the shrub layer. Notably, Artemisia had the largest relative abundance and relative frequency, values of 0.48 and 0.94, respectively, indicating it is the most abundant and widely distributed species in the sampled area and therefore a key dominant species.

Figure 11 *Relative abundance, relative height, relative coverage, and importance value of dominant species in the vegetation quadrats.*

Remote sensing provides basic variables for assessing and monitoring diversity, and establishing relationships between plant diversity and spectral data has been proposed as a potential solution (Chapungu et al., 2020; Gholizadeh et al., 2020). NDVI is frequently used to assess vegetation health, greenness, and estimate vegetation species diversity. NDVI is known for its sensitivity to primary productivity, which defines spatial variations in plant diversity (Stoms & Estes, 1993; Gillespie, 2005). Numerous studies have demonstrated significant correlations between NDVI and species diversity in various regions, such as savannah biomes (Madonsela et al., 2018) and wetlands (Zhu et al., 2022). However, our study reveals that NDVI may not always be a reliable proxy for measuring diversity, DVI can be used to establish a mathematical model for monitoring vegetation diversity at our study site. The correlation between NDVI and diversity index is comparatively low compared to DVI. Furthermore, no significant correlation between NDVI and diversity index has been observed at a 30-meter scale. This may be the heightened sensitivity of NDVI to seasonal variations, rainfall, vegetation phenology, and other environmental factors that impact biodiversity (Pau, et al., 2012; Madonsela et al., 2018). Consequently, using vegetation cover or NDVI as the primary criterion for evaluating restoration effectiveness may require further evaluation regarding validity as a tool for regulatory monitoring standards (Madonsela et al., 2018; Han et al., 2021; Mi et al., 2021; Hoffmann, 2022).

4.3 Suggestions for Monitoring of Ecological Restoration in Mining Areas

In mining areas, the restoration of vegetation diversity is of fundamental importance for establishing the biotic framework for the ecosystem to commence functioning (Huang et al., 2019; Yan et al., 2019). However, current large-scale rehabilitation operations tend to prioritize simplistic mono or poly-cultures often with a preference for fast-growing species over slower growing but more biodiverse ecosystems (Liu et al., 2018; Yang et al., 2022). It is imperative to acknowledge that natural vegetation succession, particularly in areas disturbed by mining activities, is a time-consuming process that requires meticulous planning to ensure the right species are restored that enhance successional processes (Fukami and Nakajima, 2013).

Our study findings reveal a prevalence of shrub-dominated areas, particularly in the western region, where Artemisia and Salix are the primary species. Despite providing high coverage, these areas exhibit limited species diversity (Figures 5 and 7) compared with the native reference sites (Young et al., 2022). The low diversity observed in the shrub-dominated areas may indicate a shrub encroachment phenomenon, characterized by a decrease in species richness, and landscape homogenization. Although some studies argue that this shrub encroachment represents a new equilibrium state (Peng et al., 2013), with vegetation transitioning from herbaceous to shrub-dominated, others suggest that it may lead to negative consequences such as decreased plant diversity and compromised or skewed ecological functions, including water and biodiversity conservation (Liu et al., 2021; Ding and Eldridge, 2023).

Sound monitoring that is time and cost effective is crucial to inform ecological restoration, so that timely corrective actions can be implemented and adaptive management is operationalized (Young et al., 2022). This includes thoughtful vegetation configuration, species selection, seed optimization, and planting density. Integrating vegetation diversity monitoring into the assessment criteria for evaluating the effectiveness of ecological restoration projects is essential to accurately monitor post-mining restoration success and ensure local communities are supported by robust data and validated science (Hughes et al., 2018).

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5 Conclusion

This study showed the use of unmanned aerial vehicles equipped with multispectral sensors is a promising method for identifying plant species and evaluating vegetation diversity in mining areas. The combination of UAV images, supervised classification algorithms, and field surveys proved to be a cost-effective and flexible approach for fine-scale vegetation monitoring in mine restoration projects. The findings highlight the importance of considering vegetation configuration in restoration projects, as areas dominated by shrubs tend to exhibit lower species diversity. Additionally, vegetation diversity is a critical indicator in evaluating restoration effectiveness beyond the typical focus on vegetation coverage or NDVI by mining companies. Future mine restoration efforts should enhance ecological restoration monitoring and evaluation systems in a scientifically sound manner to provide effective adaptive management that ensure restoration achieves the desired ecosystem outcomes.

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CRediT Authorship Contribution Statement

Z.X. Chen and S.L. Zhang conceived the ideas and designed methodology; Z.X. Chen, H.P. Hou, Y.J. Yang, M. Tu and Y. Yang collected the data; Z.X. Chen and H.P. Hou analysed the data; Z.X. Chen, S.L. Zhang and T. Campbell led the writing of the manuscript. Z.X. Chen, H.P. Hou, S.L. Zhang, T. Campbell, Y.J. Yang and K. Dixon wrote, reviewed and edited the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data used in this study are available from the corresponding author upon request.

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