

Article

Fusing Multispectral UAV and Satellite Imagery to Improve the Discrimination of *Vachellia karroo* in Savanna and Grassland Ecosystems

Siphokazi Ruth Gcayi ^{1,2,*} , Samuel Adewale Adelabu ¹ , Wonga Masiza ² and George Johannes Chirima ^{2,3} 

¹ Faculty of Natural and Agricultural Science, Department of Geography, University of the Free State, Bloemfontein 9300, South Africa; adelabusa@ufs.ac.za

² Geoinformatics Division, Agricultural Research Council–Natural Resource and Engineering, Arcadia 0083, South Africa; masizaw@arc.agric.za (W.M.); chirimaj@arc.agric.za (G.J.C.)

³ Centre for Geoinformation Science, Department of Geography, Geoinformatics, and Meteorology, University of Pretoria, Pretoria 0001, South Africa

* Correspondence: gcayis@arc.agric.za

Abstract

Effective control and management of the encroaching and invasive *Vachellia karroo* (*V. karroo*) in grassland and savanna biomes depends on accurate information about its spatial distribution, making remote sensing approaches essential for mapping the extent of affected areas. Although Sentinel-2 satellite data are widely used for land use and land cover applications, they often lack the spatial details required to distinguish woody species like *V. karroo*. The fusion of Sentinel-2 data with high-resolution UAV imagery offers a promising approach to enhance spectral information for species-level discrimination. This study evaluated UAV, Sentinel-2, and fused UAV–Sentinel-2 imagery for discrimination of *V. karroo* in grassland and savanna biomes of the Eastern Cape, South Africa. Field data and imagery were collected in October 2022 and classified using Random Forest (RF) and Support Vector Machine (SVM) algorithms to distinguish *V. karroo*. The findings showed that *V. karroo* was more prevalent in the savanna biome. SVM marginally outperformed RF in classifying *V. karroo* in the grassland biome, achieving overall accuracies ranging from 68.9% to 97.4%, compared to 57.8% to 97.4% for RF. Among the datasets, the fused UAV–Sentinel-2 images yielded the highest classification accuracy, with an overall accuracy of 97.4% and a kappa coefficient of 0.96. The UAV images also demonstrated high classification accuracy, with an overall accuracy of 91.67% and a kappa coefficient of 0.77, confirming its value for fine-scale mapping and reference data support. In contrast, the Sentinel-2 images produced lower classification accuracy, with an overall accuracy of 84.6% and a kappa coefficient of 0.75, mainly due to their coarser spatial resolution. Classification was more challenging in the savanna site, where mixed vegetation structure increased confusion between *V. karroo* and grass. These findings show that fused UAV–Sentinel-2 images can improve species-level discrimination, while UAV and Sentinel-2 data remain complementary for fine-scale mapping and broader monitoring of bush encroachment in grassland and savanna ecosystems.

Keywords: UAV–Sentinel-2 image fusion; bush encroachment detection; RF classification; SVM classifier; *Vachellia karroo*



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1. Introduction

Savanna and grassland ecosystems provide essential services such as carbon storage, climate regulation, and prevention of soil and water erosion while supporting diverse plant, animal, and human communities [1,2]. In South Africa, grasslands are recognized as ecosystems dominated by grasses and other herbaceous vegetation, with limited woody plant cover [3], whereas savannas are characterized by a grassy ground layer, together with a distinct woody layer of trees and shrubs [4,5]. These ecosystems cover vast areas, with savannas occupying approximately 295,000 km² and grasslands about 435,000 km² [6]. However, they are increasingly threatened by bush encroachment, particularly from woody species such as *Vachellia karroo* (*V. karroo*) [7]. Bush encroachment reduces biodiversity [8], disrupts ecosystem functions [9], and diminishes grazing capacity, negatively affecting rural livelihoods and livestock production [10]. The resulting ecological and economic losses are substantial, with estimated ecosystem service losses of up to US\$2.1 million over a 25-year period [11].

There is an urgent need for control and management measures, especially in communal areas where bush encroachment occurs at alarming rates [9–11]. Controlling bush encroachment requires accurate, up-to-date information on its spatial distribution and density. Although traditional field-based surveys are valuable, they are costly, time-consuming, and limited in spatial and temporal scope [12]. This renders them unsuitable for large-scale or long-term monitoring. Remote sensing provides a cost-effective and scalable alternative, offering repeated, wide-area observations that are essential for understanding encroachment dynamics and guiding management decisions [13,14].

The mapping of encroaching woody species relies on the ability of remote sensing systems to distinguish target species from other vegetation types. Multispectral satellite systems such as Landsat, SPOT, and Sentinel-2 have been widely used to detect and monitor woody vegetation [2,15–17]. Sentinel-2, in particular, offers freely available data with high temporal resolution and valuable red-edge bands, making it useful for vegetation studies [18]. However, its moderate spatial resolution may be insufficient for species-level discrimination, especially for woody plants like *V. karroo* that occur at rapid growth rates in mixed and heterogeneous landscapes. High-resolution commercial imagery, such as WorldView-2 and PlanetScope data, improves species discrimination but is often costly for resource-limited communities [19,20].

Unmanned Aerial Vehicles (UAVs) provide centimeter-level spatial resolution and flexible data acquisition, enabling detailed mapping and accurate ground-truth data collection [21]. However, their spatial coverage is constrained by short battery life and aviation regulations, reducing efficiency and increasing operational costs for large-scale monitoring [22,23]. Consequently, a trade-off exists between spatial detail and regional coverage: UAV imagery offers high spatial resolution but limited area coverage, whereas Sentinel-2 data provide broad coverage but insufficient resolution for species discrimination.

Recent studies have demonstrated the potential of UAV-based photogrammetry with centimeter-level accuracy for various geoscientific applications, including high-resolution mapping [24,25]. Technological advances have also enabled the application of UAVs in forestry, particularly for vegetation and forest health monitoring [24]. This study hypothesizes that the fusion of UAV and satellite datasets can overcome these limitations, providing a cost-effective and operationally feasible approach for the monitoring of bush encroachment.

The combination of UAV data with satellite imagery through image fusion offers a promising solution, integrating the high spatial detail of UAVs with the broad spatial coverage of satellites like Sentinel-2 [26]. Remote sensing image fusion methods include pixel-level, feature-level and decision-level image fusion [27]. Whilst these methods simi-

larly produce one output, they differ in application. The pixel-level fusion method focuses on merging corresponding raw pixels or bands, while feature-level fusion involves extracting features from source images and the decision-level method combines outputs from multiple sensors and or classifiers and makes one final decision [28]. For an image fusion process to be successful, an appropriate and suitable method has to be applied [29].

Several remote sensing image fusion techniques have been tested for classification [28,30,31]. For example, ref. [28] conducted a review of remote sensing spatiotemporal image fusion methods, focusing on challenges, applications and recent trends. They found that the decision-level method achieved the highest performance among compared methods. Similarly, ref. [30] compared pixel-level and feature-level image fusion techniques for the detection of slow-moving landslides and found that pixel-level fusion was outperformed by feature-level fusion. The authors of [31] compared and analyzed feature-level and decision-level data fusion methods. Their study reported that each fusion method has its advantages and disadvantages and that their success is case-dependent. The present study sought to fuse UAV and Sentinel-2 imagery to discriminate *V. karroo*. Although UAV and Sentinel-2 fusion studies have been conducted, there is still lack of studies investigating the discrimination of *V. karroo* using fused UAV–Sentinel-2 images.

Despite the potential of integrated UAV–Sentinel-2 data, no studies have investigated their use for the discrimination of *V. karroo* in South Africa’s savanna and grassland ecosystems. Machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), and others are particularly effective for the analysis of such fused datasets due to their ability to handle complex, non-linear relationships and high-dimensional data [32]. SVM is effective when working with limited training samples and imbalanced datasets, although it can be sensitive to noise [33]. RF, on the other hand, is well suited for high-dimensional datasets and can handle multicollinearity among predictor variables [32]. In grassland and savanna ecosystems, SVM and RF have been successfully applied to discriminate woody plant species and map woody vegetation [34,35]. However, no study has compared the performance of these classifiers for the mapping of *V. karroo* using UAV, Sentinel-2, and fused UAV–Sentinel-2 datasets.

This study addresses this gap by comparing UAV, Sentinel-2, and fused UAV–Sentinel-2 imagery to assess their effectiveness in mapping *V. karroo*. Specifically, the objectives were to: (i) evaluate the classification performance of UAV, Sentinel-2, and fused imagery in discriminating *V. karroo*; (ii) compare classification differences between grassland and savanna sites; (iii) compare the performance of RF and SVM classifiers in discriminating *V. karroo*; and (iv) determine the most important spectral variables for discriminating *V. karroo* from grass and bare-soil land cover types.

2. Materials and Methods

2.1. Study Area

The study was conducted in villages found in Tsolo under Mhlontlo (MLM) and in Alice under the Raymond Mhlaba (RM), local municipalities (LM) located in the Eastern Cape Province of South Africa (Figure 1). The vegetation at the sites is categorized as the Drakensberg Foothill Moist Grassland and Bhisho Thornveld of the grassland and savanna biomes [36], respectively. The study focused on two representative sites—one grassland and one savanna—for the collection of vegetation and land cover classes. Both study sites were approximately 2.5 hectares in size. This study adopted the definition of grasslands of ecosystems dominated solely by grass and that of savannas of ecosystems characterized by grass and scattered trees. Common grass species found in the study sites include *Digitaria eriantha*, *Sporobolus fimbriatus*, *Eragrostis planar*, *Heteropogon contodus*, *Themeda triander*, etc. Woody plant species that were found in the study areas include *Cordia*

rudis, *Scutia myrtina*, *Maytenus heterophylla*, etc. Photographs of the study areas are shown in Figure 2. The climate in MLM is characterized as dry sub-humid, whereas the climate in RMLM is characterized as semi-arid. The summers in MLM are warm-temperate and fully humid, whereas in RMLM, the climate is classified as hot, arid steppe [37]. Annual rainfall at the sites is received during the summer season, with an average of 749 mm in MLM [37] and above 600 mm in RMLM [38]. The dominant land uses are livestock production and livestock browsing. Some of the land is abandoned arable land that is gradually being encroached by *V. karroo*. The geology of the study sites are within the Beaufort group that falls under the Karroo Dolerite Supergroup [39]. The parent material of soil in RMLM is made from shale, sandstone, and mudstone [38], while in MLM, the soil is made from mudrocks and sandstone [40].

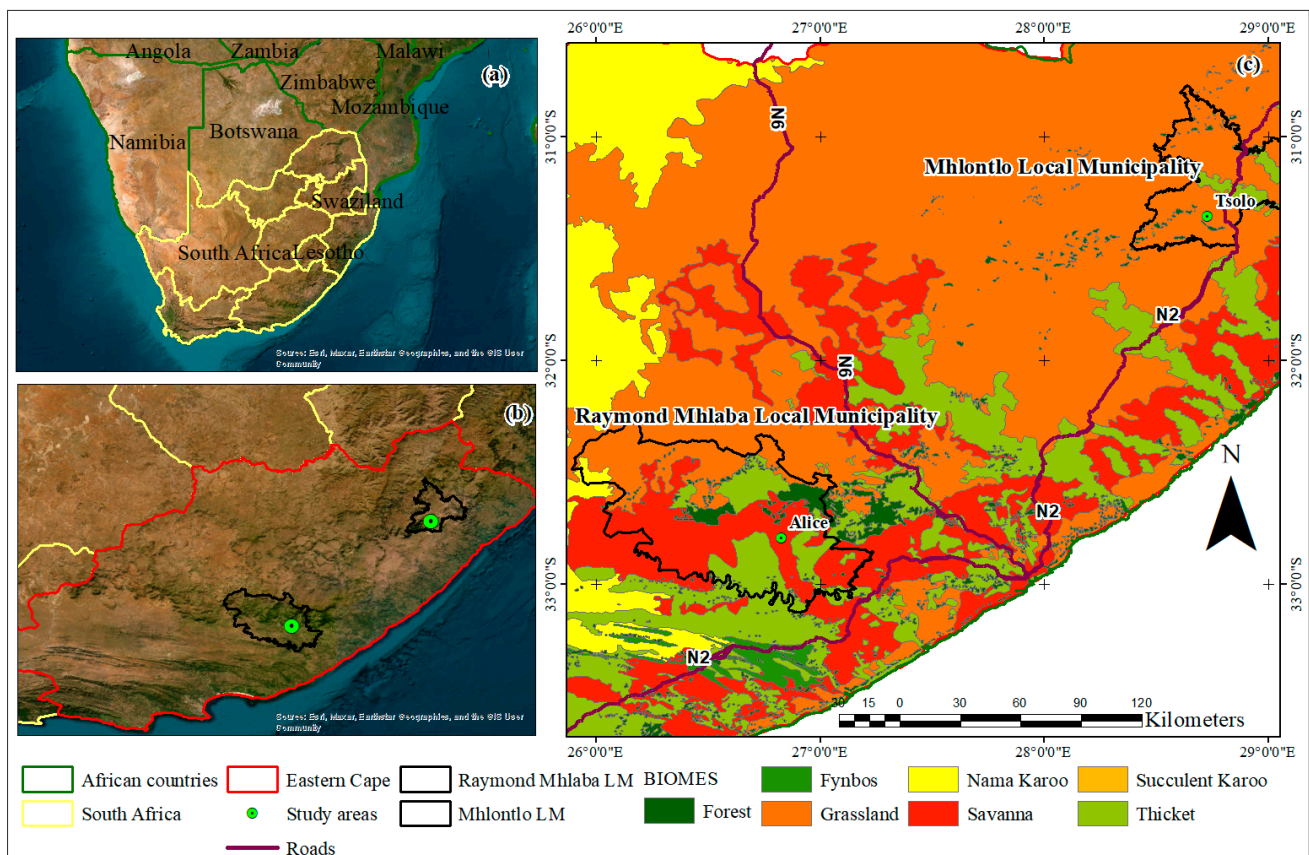


Figure 1. Location of study sites near Tsoho and Alice in the Eastern Cape province of South Africa. (a) represents the map of South Africa at an African context, (b) shows the location of the study sites within the Eastern Cape Province, (c) represents the biomes within the study sites.

2.2. Data Collection and Pre-Processing

A total of 200 ground reference data points covering different land cover types were collected in October 2022 with the aid of a Garmin GLO™ 2 Bluetooth GPS GLONASS Receiver (Garmin Ltd., Olathe, KS, USA). The GPS device was used to record the name, as well as latitude and longitude coordinates, of each land cover type shown in Table 1. Supplementary reference points (~100 points) were manually digitized from the UAV imagery across representative areas of the visible land-cover classes to improve the quality and quantity of the training data. The total number of sample points was separated into training and validation set. The numbers of training and validation samples were determined following commonly used guidelines for supervised remote sensing classification

and accuracy assessment proposed in [41]. Figure 3 presents the overall workflow adopted in this study.

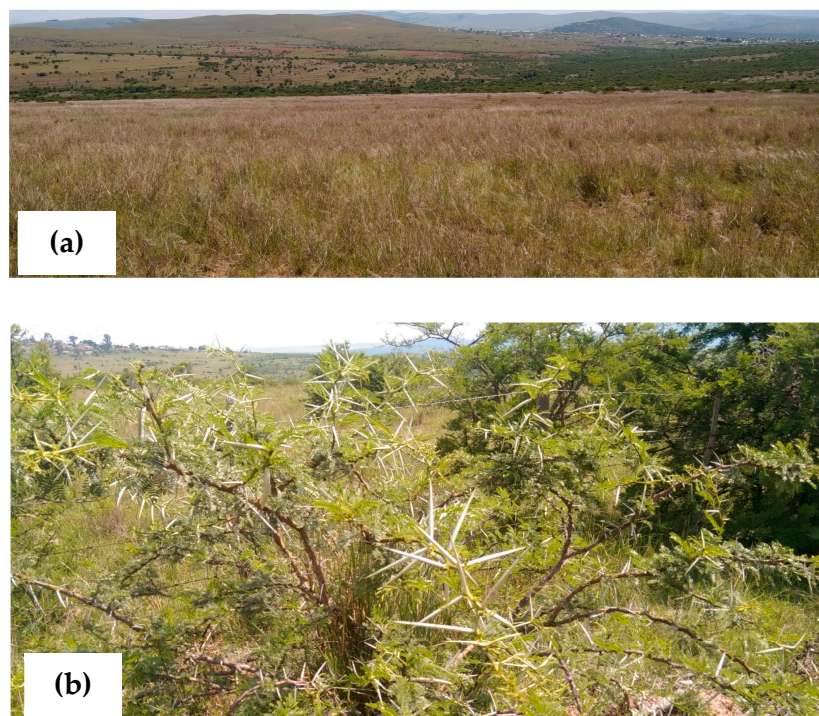


Figure 2. Photographs showing the sampling areas at the grassland (a) and savanna (b) sites.

Table 1. Reference information of *V. karroo* and other land cover classes used for training and testing in discriminating *V. karroo* using UAV, Sentinel-2 and fused images.

Land Cover Classes	Code Name	Training	Validation
<i>V. karroo</i>	Vk_grassland	35	15
	Vk_savanna	35	15
Bare Soil	Baresoil_grassland	35	15
	Baresoil_savanna	35	15
Grass	Grass_grassland	35	15
	Grass_savanna	35	15
Total samples	-	210	90

2.2.1. UAV Data Acquisition and Preprocessing

Unmanned Aerial Vehicle (UAV) imagery was acquired using a multi-rotor DJI-Matrice 600 (hereafter, UAV) mounted with a MicaSense RedEdge multispectral camera. The spectral and spatial characteristics of the imagery are listed in Table 2. The ground resolution between the sites varied between 0.103 and 0.108 m. The UAV images were projected to WGS_1984_UTM_Zone_35S and in Tag Image File Format (TIFF). UAV data acquisitions were preceded by a flight plan specifying the flight height and the boundaries of the study sites. Geometric calibration of the UAV images involved selecting ground control points within the flight path. The multispectral camera on the drone was calibrated using a Calibrated Reflectance Panel (CRP) that had white and dark colors placed in one position under the sensor before and after the flight. The calibration was performed to obtain essential camera parameters, including the focal distance, as well as distortion and sun-angle metrics. Drone2Map software for ArcGIS (version 2023.2.1) was used to process and stitch together the captured raw images.

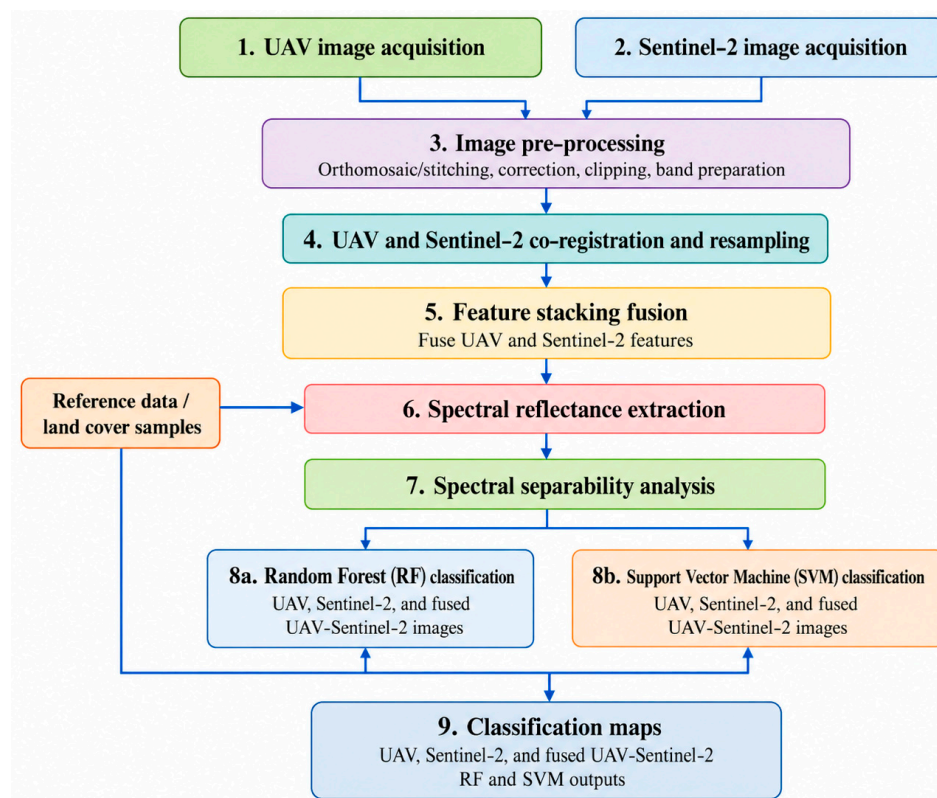


Figure 3. Flow diagram illustrating the classification workflow.

Table 2. UAV spectral characteristics and spatial resolution.

UAV Band	Center Wavelength (nm)	Bandwidth (nm)	Spatial Resolution (cm)
B1—Blue	475	20	10.3–10.8
B2—Green	560	20	10.3–10.8
B3—Red	668	10	10.3–10.8
B4—Near Infrared	840	40	10.3–10.8
B5—Red Edge	717	10	10.3–10.8
Flight Date	Sensor Type	Height Above Ground (m)	Pixel Size (cm)
20 October 2022 _{grassland}	MicaSense RedEdge-MX Sensor	120	10.3
17 October 2022 _{savanna}	MicaSense RedEdge-MX Sensor	120	10.8

2.2.2. Sentinel-2 Image Acquisition and Preprocessing

Sentinel-2 MSI images with less than 10% cloud cover were downloaded from the Copernicus Open Access Hub (<https://dataspace.copernicus.eu/analyse/apis/sentinel-hub>) (accessed on 16 November 2024) (Table 3). The acquired Sentinel-2 images coincide with the UAV data acquisition and field-visit dates (October 2022). The Sentinel-2 images obtained for the study have Level 2A surface reflectance (SR). Bands 1, 9, and 10 were excluded because they are not useful for vegetation discrimination (Table 3). All 20 m resolution bands were resampled to 10 m spatial resolution in order to match the spatial resolution of all datasets. Resampling was performed using Sentinel Application Platform (SNAP) version 10.0 software [42]. SNAP software was also used to clip the study areas using the available subset tool. The resampled image bands were stacked using Quantum GIS (QGIS) version 3.42. The output Sentinel-2 images were further aligned with the UAV images in preparation for fusion. Image fusion, classification, and statistical analysis were performed using R Studio software version 2023.12.1+402.

Table 3. Sentinel-2 sensor specifications, metadata, scene, and acquisition date.

	Band	Wavelength Range (nm)	Bandwidth (nm)	Spatial Resolution (m)
1.	B2—Blue	458–522	65	10
2.	B3—Green	543–577	35	10
3.	B4—Red	650–680	30	10
4.	B5—RedEdge1	689–712	15	20
5.	B6—RedEdge2	733–747	15	20
6.	B7—RedEdge3	773–793	20	20
7.	B8—NIR	785–899	115	10
8.	B8a—RedEdge4	855–875	20	20
9.	B11—SWIR1	1565–1655	90	20
10.	B12—SWIR2	2100–2280	180	20
Sentinel-2 Metadata				
	Month	Scene	Acquisition date	
	October 2022	S2B_MSIL2A_20221008T074809_N0400_R135_T35JPF_20221008T102958		
	October 2022	S2B_MSIL2A_20221018T074919_N0400_R135_T35HMD_20221018T102303	18 October 2022	

2.2.3. Image Fusion

Image fusion is the process of combining information from multiple source images with different spatial, spectral and temporal characteristics to produce a single image with improved spatial and spectral resolution [43]. The process of image fusion occurs at three different levels: the low level (pixel level), the intermediate level (feature level) and the highest level (decision level) [44]. This study employed feature-level fusion because feature extraction improves the quality of the input information by generating relevant and discriminative variables from the source images. Feature-level fusion focuses on extracting relevant features from the original images before the fusion process and integrates these features into a unified representation. These features may include edges, textures, shapes, spectral information and other descriptive image characteristics. In this study, feature-level fusion was implemented using the conventional feature-stacking approach, in which the original Sentinel-2 spectral bands and vegetation indices were combined with the UAV spectral bands and vegetation indices to create a single fused feature dataset for classification. Feature stacking is considered a feature-level fusion technique because it combines extracted features from multiple sources into a unified feature space prior to classification rather than fusing raw pixel values or classifier outputs. The feature-level fusion workflow comprised image preprocessing, feature stacking and generation of the fused feature dataset [45]. By retaining the original spectral bands and derived vegetation indices from both sensors as separate predictor variables, the fused feature dataset provides a more comprehensive representation of vegetation characteristics, thereby enhancing class separability and improving classification performance [46,47]. Furthermore, vegetation indices emphasize vegetation-related spectral properties, reduce background effects and provide additional discriminative variables for vegetation classification [48]. The vegetation indices incorporated into feature stacking were the normalized difference vegetation index ((NDVI) = $(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$), the normalized difference Red-Edge index ((NDRE) = $(\text{NIR} - \text{RedEdge}) / (\text{NIR} + \text{RedEdge})$) and the RedEdge Ratio index ((RRI) = $(\text{NIR} / \text{RedEdge})$).

2.2.4. Spectral Separability

Before classification, we determined whether the land cover classes were spectrally separable—an important step in classification. Determination of the spectral separability

of three land cover classes was performed for all images using the Jeffries–Matusita (J-M) statistical distance separability method. This method was selected because it is widely used in spectral separability tasks in remote sensing [49,50]. The implementation of the J-M statistical method involves computation of the average reflectance in each band for all classes and computation of the covariance matrix to determine how the band values vary, and the computation of the Bhattacharyya distance. The J-M distance ranges between zero and two, with zero indicating that classes are completely inseparable, while two indicates that classes are perfectly separable [49]. The spectral separability of the land cover classes of all images is shown in Figure 4.

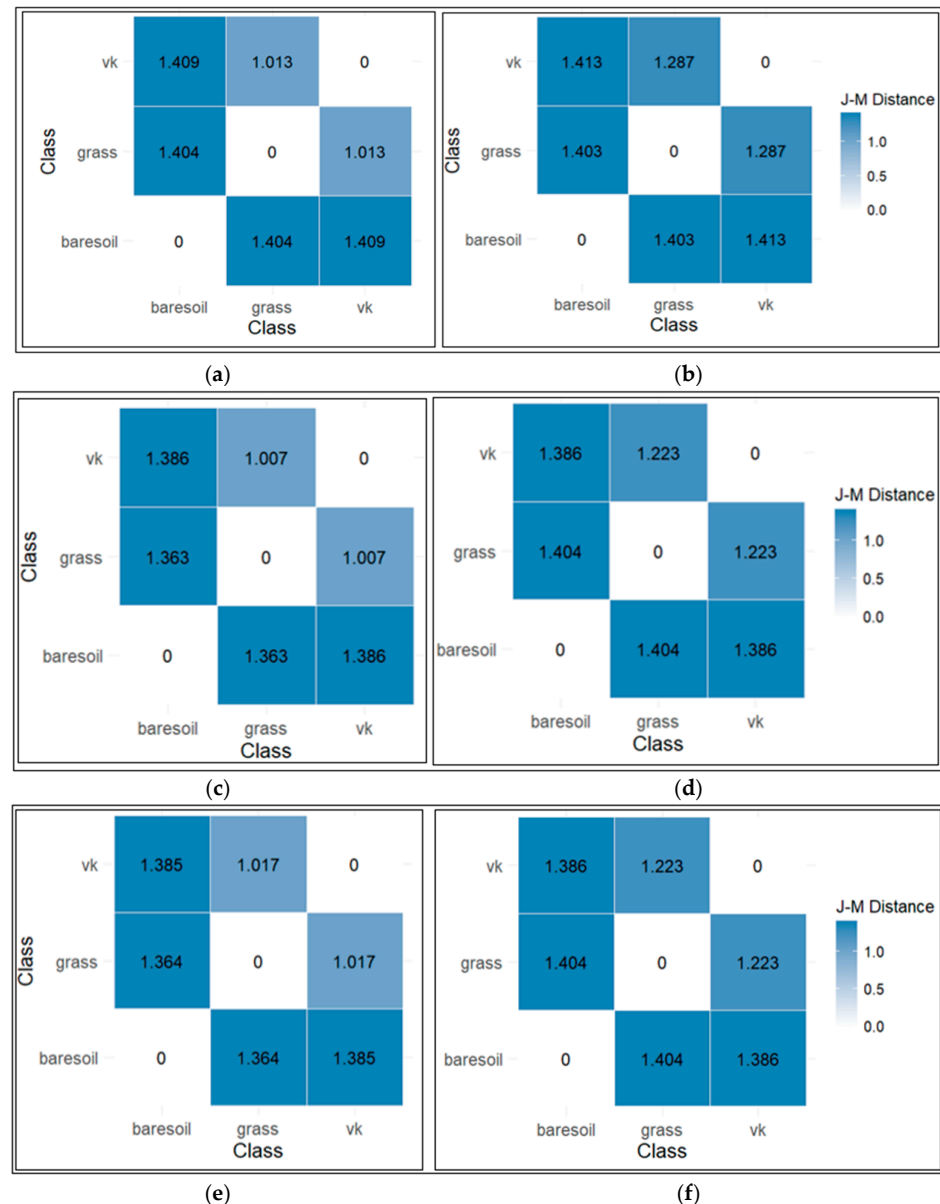


Figure 4. Jeffries–Matusita distance heat map for every pair of land cover classes derived from UAV (a,b), Sentinel-2 (c,d) and fused UAV–Sentinel-2 images (e,f) for the savanna (a,c,e) and grassland (b,d,f) sites.

2.3. Data Analysis

2.3.1. Image Classification and Accuracy Assessment

The random forest (RF) and support vector machine (SVM) classification methods were used to discriminate *V. karroo* from other land cover types at the grassland (denoted as

_grassland) and savanna (denoted as _savanna) sites. The RF method was chosen because it avoids model overfitting [51] and therefore produces reliable classification performance. RF is a classification and regression machine learning algorithm developed in [52]. For classification, the RF creates a group of independent tree-like classifiers that are evenly distributed, and every tree can vote for a popular class. The group of trees is randomly selected from a bootstrap sample. Each tree in a random forest has a node, which is divided using the best randomly selected predictors [53]. RF requires the tuning of two parameters: *ntree*, which is the number of trees in a forest, and *mtry*, which is the number of variables in the random subset at each node [52]. RF is implemented by drawing a bootstrap sample from the original data, with the random forest grown unpruned. Two-thirds (in-bag) of the bootstrap sample data are used for model training, and the remaining one-third (out-of-bag (OOB)) is used to validate the model. At the end, the RF algorithm aggregates the total votes from all trees to obtain the overall prediction. The RF model has an embedded variable importance measure that assesses the contribution of each variable to the classification process. These measures include the permutation variable importance measure and the Gini index. In this study, the permutation variable importance method was used to identify the important variables for classification. The randomForest package was used to implement RF in R statistical software.

The Support Vector Machine (SVM) algorithm is also used for both classification and regression problems. It is based on the statistical learning theory and uses few samples in the training of the model to obtain the best classification results. In a classification, SVM changes the original data space by finding the best hyperplane that separates the data into different classes [51]. That hyperplane is further widened to increase the distance between the classified vectors. SVM requires tuning of the gamma (γ) and C parameters for regularization of the model [54]. The purpose of optimization is to determine the best parameters that the classifier can use to accurately classify land cover from unknown data. The advantages of SVM are its abilities to generalize, discriminate and provide the best solution [55]. This algorithm identifies small patterns in a dataset [56], which makes it good at classification. In a classification, SVM discriminates features by following the examples of classification predictions from unseen data [56]. SVM improves classifications by using kernel functions. These kernel functions include linear, polynomial, radial and sigmoid functions [57]. This study used the radial basis function (RBF), as it is widely used in classification studies due to its robust performance [58,59]. The RBF equation can be defined as shown below [59].

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0 \quad (1)$$

where γ is the gamma parameter that controls the width of the kernel function, $K(x_i, x_j)$ is the kernel function, and $\|x_i - x_j\|^2$ is the squared Euclidean distance between x and x' . The accuracy of the SVM classifier with RBF depends on the tuning of the gamma and cost (C) parameters [60,61]. For this study, 5-fold cross-validation was used to overcome overfitting problems, following [62]. The best γ and C values were used to train the SVM model. The SVM method was selected because of its flexible kernel functions, strong generalization ability, and regularization capacity, which help reduce overfitting and improve classification performance [51,55]. The e1017 package in R software was used to implement SVM classification. For both the RF and SVM classifications, the UAV bands (5), Sentinel-2 bands (10), and fused image bands (10) were used as the predictor variables.

2.3.2. Accuracy Assessment

The study used the split sample method for validation, with reference data split in a ratio of 70% for training and 30% for validation. The split was performed randomly

using a stratified technique to ensure that class proportions were preserved [63]. For the UAV-based classification, the bare soil class was excluded from the validation dataset to avoid data leakage and reduce the risk of model overfitting, as some bare soil samples were generated through visual interpretation of the UAV imagery. Accuracy measures, including the overall, producer and user accuracies, as well as κ , were computed from an error matrix to evaluate the performance of the RF and SVM models.

2.3.3. Variable Importance

RF is able to evaluate the contribution of the predictor variables during classification using the variable selection method [32]. This study used the mean decrease in Gini to rank the spectral bands in their order of importance for the classification. The mean decrease in Gini was computed with the equation below [64]:

$$VI_{perm}(x_j) = \frac{1}{K} \sum_{k=1}^K VI_{gini}^k(x_j) \quad (2)$$

where $VI_{perm}(x_j)$ is the forest-level variable importance score, K is the number of trees in the random forest, $\sum_{k=1}^K$ is the sum of all trees, and $VI_{gini}^k(x_j)$ is the per-tree Gini importance.

3. Results

3.1. Performance of UAV, Sentinel-2, and Fused UAV–Sentinel-2 in Discriminating *V. karroo*

Figure 5 shows the original UAV, Sentinel-2, and fused UAV–Sentinel-2 images for the savanna and grassland sites. Figures 6 and 7 show the classification maps produced using the RF and SVM classifiers, respectively, from the UAV, Sentinel-2, and fused datasets.

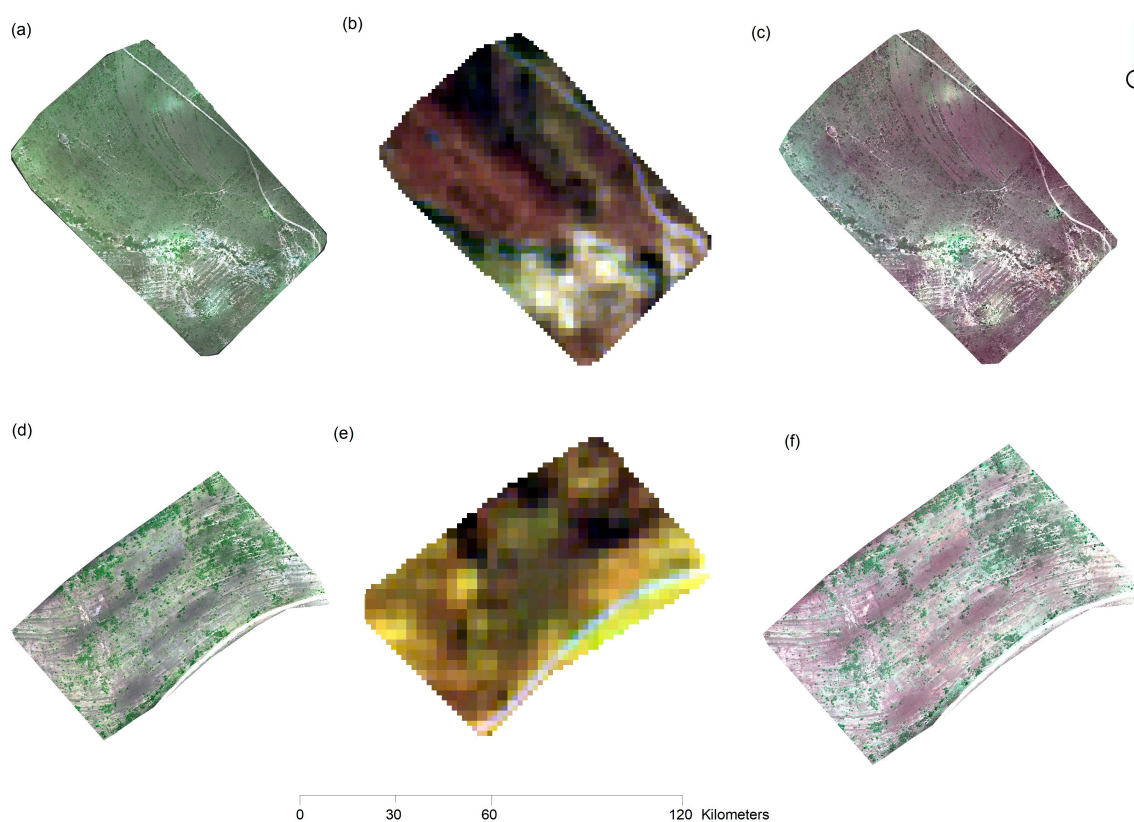


Figure 5. Original UAV (a,d), Sentinel-2 (b,e) and fused UAV–Sentinel-2 (c,f) images of the study sites in the savanna (a–c) and grassland (d–f) biomes.

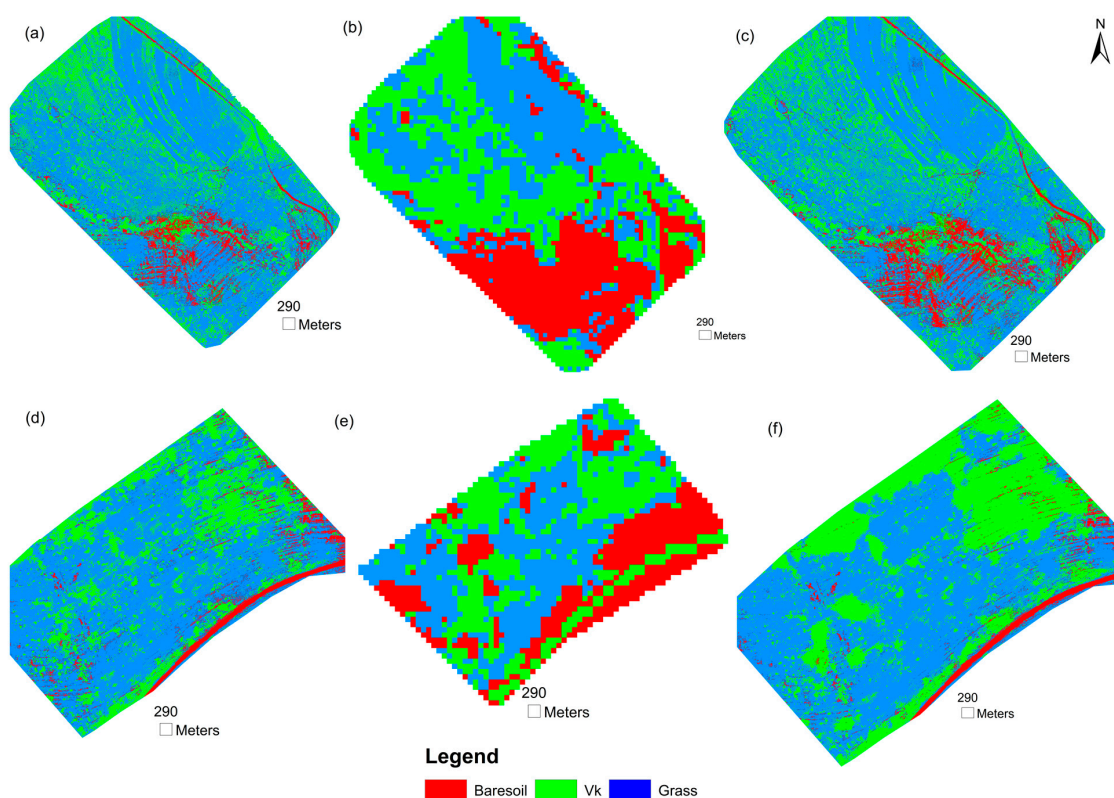


Figure 6. RF classification maps derived from UAV (a,d), Sentinel-2 (b,e) and fused UAV–Sentinel-2 (c,f) images of the study sites in the savanna and grassland biomes. Panels (a,c,e) represent the savanna site, while panels (b,d,f) represent the grassland site.

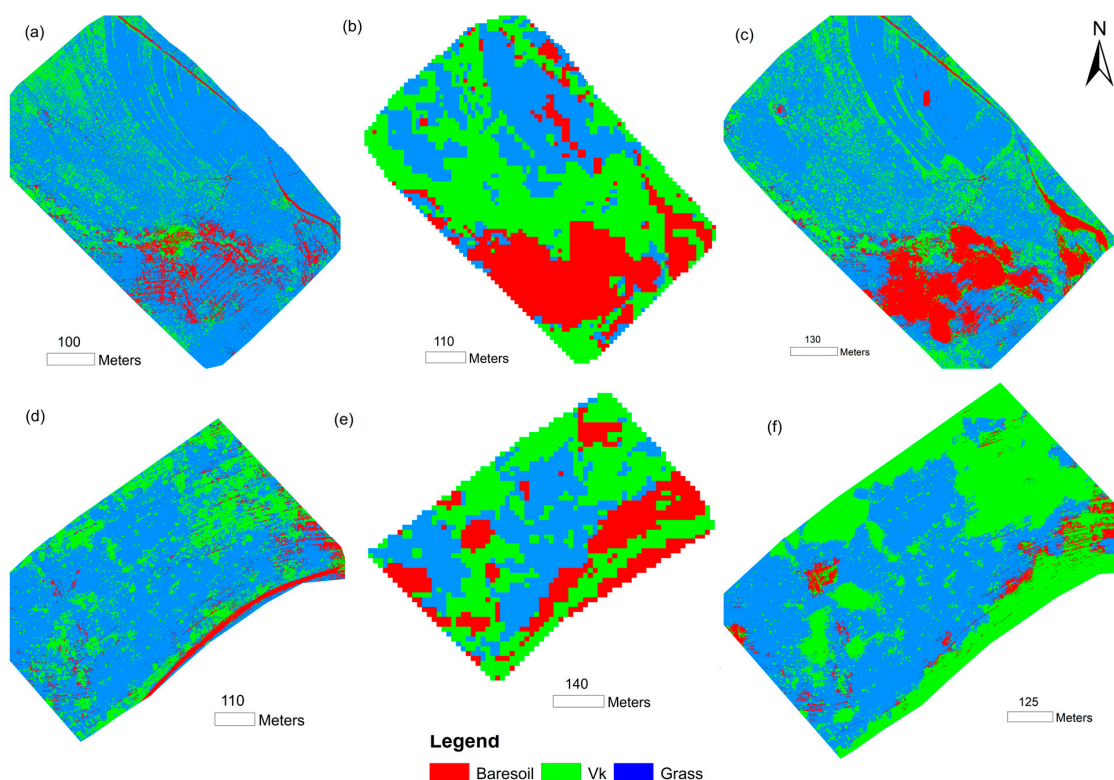


Figure 7. SVM classification maps derived from UAV (a,d), Sentinel-2 (b,e) and fused UAV–Sentinel-2 (c,f) images of the study sites in the savanna and grassland biomes. Panels (a,c,e) represent the savanna site, while panels (b,d,f) represent the grassland site.

3.2. Classification of Grassland and Savanna Biomes

Tables 4 and 5 show the statistical results of the RF and SVM classifiers, respectively, derived from UAV, Sentinel-2 and fused images. For the RF classification (Table 4), the results show that the grassland site (land cover type denoted as _grassland) had better results than the savanna site (land cover type denoted as _savanna) for the UAV, Sentinel-2 and fused images (here onwards, all datasets). The producer's (PA) and user's (UA) accuracies for the grassland site ranged between 71.4% and 100% (UAV image), 50% and 94.1% (Sentinel-2 image), and 87.5% and 100% (fused image). For the savanna site, PA and UA ranged between 71.4% and 100% for the UAV image, 38.9% and 100% for the Sentinel-2 image, and 78.6% and 100% for the fused image. The 100% accuracy values should be interpreted with caution, as they reflect model performance based on the available validation samples rather than error-free classification across the entire study area. These values may be influenced by factors such as the limited validation sample size, spatial autocorrelation, and strong spectral separability among the sampled classes.

Table 4. Random forest classification results of UAV Sentinel-2 and fused images.

Land Cover	UAV Image		Sentinel-2 Image		Fused Image	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
<i>V. karroo</i> _grassland	71.4	100	57.1	66.7	100	100
<i>V. karroo</i> _savanna	93.8	93.8	50.0	38.9	78.6	100
Grass_grassland	100	89.4	86.7	81.2	100	93.8
Grass_savanna	92.9	92.9	43.8	50.0	100	84.2
Bare soil_grassland	-	-	94.1	94.1	94.1	100
Bare soil_savanna	-	-	80.0	92.3	100	100
OA_grassland (%)	91.7		84.6		97.4	
OA_savanna (%)	93.3		57.8		93.3	
Kappa_grassland	0.78		0.75		0.96	
Kappa_savanna	0.87		0.37		0.89	

Table 5. SVM classification results of UAV, Sentinel-2 and fused images for grassland and savanna biomes.

Land Cover	UAV Image		Sentinel-2 Image		Fused Image	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
<i>V. karroo</i> _grassland	71.4	100	57.1	50.0	100	87.5
<i>V. karroo</i> _savanna	87.5	100	78.6	50.0	78.6	100
Grass_grassland	100	89.5	73.3	78.6	100	100
Grass_savanna	100	87.5	43.8	70.0	100	84.2
Bare soil_grassland	-	-	94.1	94.1	94.1	100
Bare soil_savanna	-	-	86.7	100	100	100
OA_grassland (%)	91.6		79.5		97.4	
OA_savanna (%)	93.3		68.9		93.3	
Kappa_grassland	0.78		0.68		0.96	
Kappa_savanna	0.87		0.54		0.89	

The results also reveal that bare soil was better classified than other land cover types, with high PA and UA between 80% to 100% across all datasets. *V. karroo* in the grassland site (Table 4) obtained the highest classification accuracies in the fused image, with PA and UA of 100%. The highest overall accuracies (OAs) for the grassland site for the UAV, Sentinel-2 and fused images were 91.6%, 84.6% and 97.4% respectively, with kappa (κ) values of 0.78, 0.75 and 0.96 respectively, whereas for the savanna site, the highest OAs were 93.3% for UAV, 68.9% for Sentinel-2 and 93.3% for the fused images, with κ values

of 0.87 (UAV image), 0.54 (Sentinel-2) and 0.89 (fused images). In comparison with all the datasets (UAV, Sentinel-2 and fused images), the fused UAV–Sentinel-2 image had the best results, followed by UAV and, lastly, Sentinel-2. This indicates that *V. karroo* can be best discriminated with fused UAV–Sentinel-2, followed by UAV.

The statistical results of the SVM classifier in Table 5 generally show that the fused image had better classification results than the UAV and Sentinel-2 datasets. Similar to RF, SVM classification results from the grassland site (for the fused image) were higher compared to the savanna site, with PA and UA between 87.5% and 100%, OA = 97.4% and κ = 0.959 (for grassland), compared to PA and UA between 78.6% and 100%, OA = 93.3% and κ = 0.899 for the savanna site. The classification results from the savanna site (from the UAV image) (PA and UA between 87.5% and 100%, OA of 93.3% and κ of 0.86) are better than those from the grassland site, with PA and UA between 71.4% and 100%, OA of 91.6% and κ of 0.77. Sentinel-2 classification results were lower than those of the UAV and fused images, with PA and UA for the grassland biome ranging between 57.1% and 94.1%, OA = 79.5% and κ = 0.68. For the savanna site, PA and UA were between 43.8% and 100%, OA = 68.9% and κ = 0.54. The classification results from the fused images show that the grassland site generally had better results than the savanna site.

3.3. Comparison of RF and SVM

RF and SVM displayed similar performance for the UAV and fused images, while RF showed better performance than SVM for the Sentinel-2 image. The models displayed differences in classifier performance between the grassland and savanna sites. This may be linked to the variation in landscape heterogeneity, as the savanna site is more structurally complex, with greater mixing of woody vegetation, grass, bare soil, and shadows, which may increase spectral overlap among classes and reduce classification accuracy.

Tables 6 and 7 show the confusion matrix of the classified land cover types using RF and SVM classifiers. The results show that there were few misclassifications of bare soil (for Sentinel-2 and fused images). Misclassifications of bare soil occurred in the grassland site under the Sentinel-2 data only. There were several misclassifications of grass land cover across all datasets, with grass mostly misclassified as both *V. karroo* and bare soil for both the grassland and savanna sites. More misclassifications occurred for the savanna site than the grassland site. There were no misclassifications of *V. karroo* in the UAV and fused images of the grassland site; however, the Sentinel-2 image showed misclassifications. For the savanna site, *V. karroo* was misclassified in the Sentinel-2 dataset. The SVM confusion matrix in Table 7 shows that there were no misclassifications of the bare soil land cover type for either the grassland or savanna site in the fused image; however, the Sentinel-2 had misclassified bare soil as grass (grassland site) and *Vk* (savanna site). The grass and *V. karroo* land cover types at the study sites were misclassified as one another across all datasets. Overall, the confusion matrix shows that the RF classifier produced more misclassifications than the SVM classifier when using the Sentinel-2 image.

3.4. Variable Importance of Predictors in Discriminating *V. karroo*

Figure 8 shows the variable importance produced by the RF classifier from the classification of UAV (a and d), Sentinel-2 (b and e) and fused images (c and f) of the grassland and savanna sites. The variable importance measures the increase in prediction error when a predictor variable is removed. This was evaluated for all variables in each dataset in order to assess their contributions in discriminating *V. karroo*. The fused-image predictor variables consisted of both UAV- and Sentinel-2-derived variables used in the classification. The UAV-derived variables are denoted by the prefix U_, while the Sentinel-2-derived variables are denoted by the prefix S_. Generally, the red band was found to be the most common

and important variable across all datasets for both the RF and SVM classifiers. Other bands that were important from the UAV classification included the blue and green bands. For Sentinel-2, B6 and B4 were additional important bands. For the fused image, vegetation indices (NDVI, NDRE and RER) and the red and blue bands were most important in the classification. In the UAV classification, the NIR and RedEdge bands showed little contribution, while in the Sentinel-2 and fused images, the RedEdge bands also showed less contribution in the classification.

Table 6. Random forest confusion matrix of UAV, Sentinel-2 and fused images for grassland and savanna biomes.

Reference										
Prediction	UAV Images			Sentinel-2 Images			Fused Images			
	Land Cover Type	Bare Soil	Grass	Vk	Bare Soil	Grass	Vk	Bare Soil	Grass	Vk
	Baresoil_grassland	-	-	-	16	1	0	16	0	0
	Baresoil_savanna	-	-	-	12	0	1	15	0	0
	Grass_grassland	0	17	2	0	13	3	1	15	0
	Grass_savanna	0	13	1	1	7	6	0	16	3
	Vk_grassland	0	0	5	1	1	4	0	0	7
	Vk_savanna	0	1	15	2	9	7	0	0	11

Table 7. SVM confusion matrix of UAV, Sentinel-2 and fused images for grassland and savanna biomes.

Prediction	Reference									
	UAV Images			Sentinel-2 Images			Fused Images			
	Land Cover Type	Bare Soil	Grass	Vk	Bare Soil	Grass	Vk	Bare Soil	Grass	Vk
	Baresoil_grassland	-	-	-	16	1	0	16	0	0
	Baresoil_savanna	-	-	-	13	0	0	15	0	0
Grass_grassland	0	17	2	0	11	3	0	15	0	
Grass_savanna	0	14	2	0	7	3	0	16	3	
Vk_grassland	0	0	5	1	3	4	1	0	7	
Vk_savanna	0	0	14	2	9	11	0	0	11	

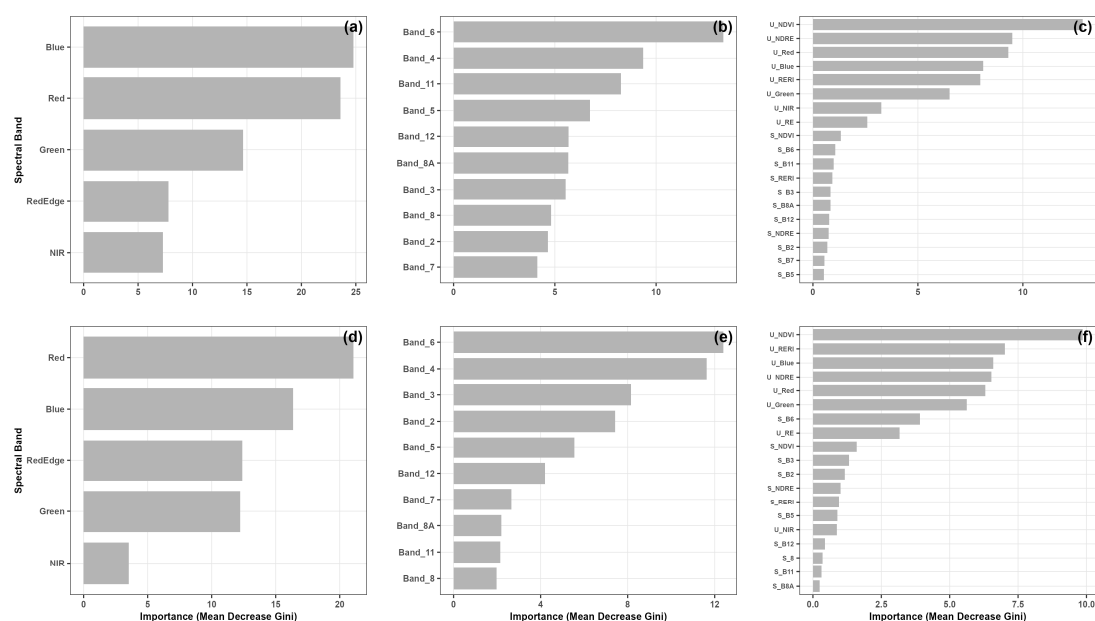


Figure 8. Variable importance of UAV (a,d), Sentinel-2 (b,e) and fused images (c,f) derived from the RF classifier for the savanna (a–c) and grassland (d–f) sites.

4. Discussion

Encroaching woody species are threatening the biodiversity and functioning of indigenous savannas and grasslands, and identifying these species is key for effective monitoring and management. This study assessed the performance of UAV, Sentinel-2 and fused UAV–Sentinel-2 images in discriminating the encroaching and invasive *Vachellia karroo* from grass and bare soil land cover types using random forest (RF) and support vector machine (SVM) classifiers. Our findings demonstrate that the fused UAV–Sentinel-2 image provided the highest classification capability for this purpose in both grassland and savanna sites with the use of the SVM classifier, which marginally outperformed RF.

4.1. Performance of UAV–Sentinel-2, UAV and Sentinel-2 Images in Discriminating *V. karroo*

The fused UAV–Sentinel-2 image achieved the highest overall accuracy (OA) in discriminating *V. karroo* at both grassland and savanna sites, confirming its effectiveness for fine-scale vegetation mapping. At the grassland site, classification accuracies were higher (OA = 97.4% for both RF and SVM). The superior performance of the fused UAV–Sentinel-2 image was likely due to the integration of complementary spatial and spectral information, with the fine spatial detail of the UAV data and the broader spectral information from Sentinel-2 improving class separability and reducing misclassification. The relative homogeneity of the grassland site may have also made it easier for the fused image to detect *V. karroo*, as the improved spatial resolution increased the distinction between *V. karroo* and the surrounding land cover classes. Our findings are consistent with [65], which reported high classification accuracies from fused images when detecting grazing intensity. The abovementioned study obtained an OA of 92.13%, outperforming the original datasets. Similarly, ref. [66] reduced the mean absolute percentage error (MAPE) from 54.3% to 10.01% in detecting mining areas. Ref. [67] obtained an accuracy of 85.4% in classifying crop types using fused UAV–Sentinel-2 data. Although the areas of application of these studies differ from those of our study, they demonstrate the potential of image fusion in improving classification and detection accuracy by combining complementary information from different sensors.

In contrast, our findings differ from those reported in [35], in which improved classification accuracy was not obtained from fused Sentinel-1 and Sentinel-2 data. The difference in performance may be attributed to the spatial resolution of the fused datasets. Although the fusion of Sentinel-1 and Sentinel-2 imagery combines different types of remote sensing information, the resulting spatial resolution may still be too coarse for detection of woody invasive species at the species level. This further highlights the limited number of studies that have specifically fused UAV imagery with Sentinel-2 or other coarser-resolution satellite imagery for the mapping, detection, or discrimination woody plant species. Most existing studies have used either UAV or satellite imagery independently or compared their performance without integrating them through image fusion. Therefore, the present study contributes to this gap by demonstrating the potential of fused UAV–Sentinel-2 imagery for the discrimination of *V. karroo* in grassland and savanna environments.

At the savanna site, classification accuracies were relatively lower (OA = 93.3% for both RF and SVM) compared to the grassland site, likely due to the heterogeneous vegetation structure, as *V. karroo* coexists with grasses and other woody species. The coexistence of *V. karroo* with grasses and other woody species may have increased spectral mixing, thereby reducing class separability. Similar trends were observed by the authors of [68], who reported reduced accuracy in savanna woodlands compared to more homogeneous grasslands. Because the fused image includes coarse Sentinel-2 characteristics, the product image may have inherited some limitations from Sentinel-2. Our study obtained higher classification results in comparison with those reported for woody species classification

at savanna sites in [69] and [70] (76% and 86% OA, respectively) using fused Sentinel-1 and Sentinel-2 data. The better performance achieved in this study highlights the potential of fused UAV–Sentinel-2 imagery for targeted species detection in savanna and similar heterogeneous ecosystems.

The UAV image ranked second in classification performance, outperforming the Sentinel-2 image but producing slightly lower accuracy than the fused UAV–Sentinel-2 dataset. The UAV dataset showed the highest classification accuracy for the savanna site (OA = 93.3 for both RF and SVM) in comparison with the grassland site (OA = 91.67 for both RF and SVM). This result suggests that the savanna site benefited more from the UAV’s fine spatial detail. Similar results were reported in [67], with UAV images outperforming Sentinel-2 images but achieving lower accuracy than the fused image. Another similar finding was reported by the authors of [71], who also found UAV-based vegetation indices to be more detailed than Sentinel-2 maps in evaluating habitat conditions. Considering the fine spatial resolution of 10 cm, the UAV image provides confidence in detecting *V. karroo* at the species level, particularly in heterogeneous landscapes, where fine spatial detail is required to distinguish individual woody plants from surrounding vegetation.

The Sentinel-2 image produced the lowest classification accuracies, particularly at the savanna site, with OAs of 57.78% for RF and 68.89% for SVM. Although the Sentinel-2 image is useful for broad-scale land cover mapping, its moderate spatial resolution limited its ability to detect individual *V. karroo* plants, especially in the heterogeneous savanna landscape, where woody vegetation, grass, bare soil, and shadows often occur within the same pixel. This poor performance might have also been affected by the relatively limited sample size, even though the samples were within the range of minimum recommended sample size required for classification. The limited sample size might have reduced ability of the Sentinel-2 model to capture the full spectral variability within each class. Despite its limitations as an individual dataset, Sentinel-2 provided complementary spectral information that enhanced classification when fused with the high spatial resolution of the UAV image. These findings are consistent with [67], which reported lower accuracy levels for Sentinel-2 images compared to UAV and fused images, with Sentinel-2 achieving an accuracy of 71%. According to [69], the accuracy of a classification needs to be assessed in parallel with the spatial image resolution, with smaller cell sizes preferred, as they limit chances of mixed pixels. In line with this, our findings show that Sentinel-2 alone is not suitable for species-level discrimination of *V. karroo*.

Performance of Datasets and Their Operational Applicability

The evaluation of UAV, Sentinel-2 and fused UAV–Sentinel-2 data supports previous studies showing that remote sensing data are not equally effective across landscape scales [72]. The results of our study show that both UAV and fused UAV–Sentinel-2 images have potential for the monitoring of the encroachment of *V. karroo* in Eastern Cape grasslands, savannas and similar ecosystems. However, UAV data are limited by high acquisition costs and restricted spatial and temporal coverage. Therefore, a UAV image may be more useful in supporting the collection and interpretation of ground-truth sampling points for the training of classification models.

For practical applications, fused UAV–Sentinel-2 data could be used for the mapping and monitoring of the invasion and encroachment of *V. karroo*. This is mainly because Sentinel-2 data are freely available and provide large-area coverage. The poor performance of Sentinel-2 in this study suggests that it may be more useful when combined with higher-resolution UAV data rather than being used independently for species-level mapping. The coarse spatial resolution of Sentinel-2 introduces mapping uncertainties in heterogeneous ecosystems such as savannas [70]. Although existing remote sensing data are valuable

for the monitoring of woody plants, their coarse resolution remains a challenge for the detection of woody plants at the species level [73]. Therefore, image fusion techniques offer a useful way of exploiting archived satellite data while improving the information available for classification.

4.2. Differences Between Grassland and Savanna Biomes

Across all datasets and classifiers, *V. karroo* in the grassland site was better classified/mapped compared to the savanna biome. This can be attributed to the structural simplicity and semi-homogeneity of grasslands, where *V. karroo* plants are more visually distinct against the grassy background. In contrast, savannas are more heterogeneous, with mixed vegetation species that create spectral overlap between classes. The taller canopy of *V. karroo* can overshadow grasses, further complicating spectral discrimination. Similar challenges have been reported in studies mapping invasive woody species in heterogeneous landscapes [68,74]. The confusion between grass and *V. karroo* is ecologically important because it affects the reliability of detection of early woody encroachment. When *V. karroo* is misclassified as grass, the extent of bush encroachment may be underestimated, which could delay management interventions. Conversely, when grass is misclassified as *V. karroo*, the level of encroachment may be overestimated, leading to inaccurate assessments of rangeland condition. This confusion is particularly important in savannas, where mixed vegetation structure and canopy overlap reduce spectral separability between woody plants and grasses. Therefore, class-level errors provide important ecological information because they indicate whether the target shrub can be reliably separated from background vegetation in structurally complex landscapes. These results highlight the need for biome-specific approaches whereby grasslands can be effectively monitored using medium-resolution sensors like Sentinel-2 and others, while savannas may require higher-resolution UAV or commercial images for accurate mapping.

4.3. Comparison of RF and SVM

The SVM classifier marginally outperformed RF, particularly when applied to UAV images. This is likely due to SVM's sensitivity to high-resolution data and its ability to handle small training datasets and complex class boundaries [55]. RF, which relies on decision-tree ensembles, tends to perform better on lower-resolution data but may struggle with fine-scale heterogeneity [75]. Despite these differences, the Wilcoxon signed-rank test revealed no statistically significant difference ($p > 0.05$) between the performances of the two classifiers in terms of overall accuracy and Kappa coefficient. This suggests that both algorithms are viable options for woody species discrimination, with SVM offering slightly better performance in high-resolution applications.

4.4. The Importance of Input Variables

Analyses of variable importance highlight the red and blue spectral bands as the most critical for discriminating *V. karroo* from grass and bare soil. These bands correspond to regions of strong chlorophyll absorption, reflecting differences in pigment concentration and leaf structure between *V. karroo* and surrounding vegetation [72,76]. The RedEdge and NIR bands contributed less, likely due to lower chlorophyll concentrations and incomplete canopy development during the spring season. These results align with previous studies showing seasonal variability in the importance of spectral regions for vegetation discrimination [76]. For operational monitoring, vegetation indices incorporating red and blue bands, such as the Enhanced Vegetation Index (EVI), may provide improved separability during early growing seasons.

4.5. Limitations and Future Directions

This study has several limitations that may have influenced classification performance. Although the number of training and validation samples was within the recommended minimum requirement, the relatively limited sample size may have reduced the ability of the models to capture within-class spectral variability, particularly at the heterogeneous savanna site. In addition, the moderate spatial resolution of Sentinel-2 imagery may have resulted in mixed-pixel effects caused by the spatial co-occurrence of woody vegetation, grass, and bare soil, thereby limiting its ability to detect individual *V. karroo* plants. The fusion approach used in this study may have also influenced the classification results, as a simple fusion method may not fully retain both the fine spatial detail of UAV imagery and the spectral information of Sentinel-2 imagery.

Future studies should include a larger number of independent training and validation samples; test alternative image fusion techniques; and incorporate additional data sources, such as multi-temporal imagery, vegetation indices, LiDAR, or SAR data. Applying the approach across different seasons, sites, and vegetation conditions would also improve understanding of the transferability of the models for the monitoring of woody plant encroachment.

5. Conclusions

Savanna and grassland ecosystems are increasingly facing degradation due to bush encroachment, and discriminating encroaching *V. karroo* is necessary for effective monitoring and management. This study compared UAV, Sentinel-2 and fused UAV–Sentinel-2 imagery for the discrimination of *V. karroo* at selected grassland and savanna sites using RF and SVM classifiers. The findings show that the fused UAV–Sentinel-2 image produced the highest classification performance, followed by the UAV image, while Sentinel-2 produced the lowest accuracies, particularly in the savanna site. However, the UAV image remained highly useful for fine-scale mapping and in terms of supporting the collection of high-quality reference samples, whereas Sentinel-2 remains valuable for broader-scale monitoring because of its free availability and large-area coverage. The lower performance of Sentinel-2 in the savanna site highlights the difficulty of separating *V. karroo* from grass and other vegetation in heterogeneous landscapes. The red and blue bands show strong potential for the discrimination of *V. karroo*, suggesting that their inclusion in classification models may improve class separability. Overall, the results indicate that UAV and Sentinel-2 data can play complementary roles in the monitoring of *V. karroo*, but further research using larger study areas, additional seasons and alternative fusion approaches is needed to improve species-level discrimination in complex savanna environments.

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