A combination of Sentinel-1 RADAR and Sentinel-2 multispectral data improves classification of morphologically similar savanna woody plants

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ABSTRACT
The co-existence of diverse plant forms in densely vegetated savanna environments presents a challenge when mapping species diversity using single remotely sensed data type that carries either optical or structural information. In the present study, Sentinel-1 RADAR and Sentinel-2 multispectral data were combined to classify morphologically similar woody plant species (n = 27) and three coexisting land cover types using Deep Neural Network (DNN). The fused image recorded a higher overall classification accuracy (76%) than the sole use of Sentinel-2 (72%) and Sentinel-1 RADAR data (71%). Slightly more species (15) recorded accuracies exceeding 75% using fused image compared to Sentinel-2 and Sentinel-1 data (13 species > 75%). Analysis of relative band contributions resulted in high importance from Sentinel-1 C-band ratio of VH/VV polarization (8.6%) as well as a select Sentinel-2 bands (Near infrared (9.86%), Shortwave (9.5%), and Vegetation red edge (8%)). Parallel to continual efforts to improve the accuracies of fused RADAR–optical data, the services of such data for regional-scale applications should be explored to inform timely biodiversity assessments.

INTRODUCTION
Savanna vegetation is generally characterized by complex plant structures, ranging from grass communities to large woody plant species (Hanan et al., 2010; LeVine & Crews, 2019; Pennington et al., 2018). Such complexity indicates the intricate ecosystem services that savannas provide to a given environment (Adole et al., 2016; Arekhi et al., 2017; Ashton & Zhu, 2020). Timeous and accurate assessment of species diversity assists ecologists in management efforts that seek to sustain these ecosystem services. Field-based monitoring methods unfortunately remain inefficient due to their inability to provide a blanket coverage as well as the high cost involved for large spatial coverage and continuous assessment. Remote sensing is proving crucial in the management and conservation of biodiversity (Pettorelli et al., 2018). Utilisation of remotely sensed data in these environments thus can play an important role in efforts to sustain biodiversity and derive ecological benefits. The continuous improvement and availability of remotely sensed data provide the opportunity for accurate mapping of woody plant species (Bartsch et al., 2020; Joshi et al., 2016; Kulkarni & Rege, 2020; Taddeo et al., 2019)

Optical remote sensing uses spectral information in the shortwave region of the electromagnetic energy to distinguish plant species (Rocchini et al., 2018). Variability captured in the optical remote sensing signal is correlated with plant species diversity (LeVine & Crews, 2019). Several studies have applied multispectral data with high spatial and spectral resolution to discriminate plant species at relatively high accuracies (Cross et al., 2019; Falcioni et al., 2020; Jay et al., 2019; Taureau et al., 2019; Wagner et al., 2019; Yan et al., 2018). However, limited access to such data continues to constrain their extensive applications needed for efficient ecological management. Although more high-spatial resolution data such as Planet are becoming publicly available, multispectral data with moderate spectral and spatial characteristics remain the common source of information for biodiversity assessment (Humagain et al., 2017). A fundamental challenge of using optical remote sensing for biodiversity assessment is that it suffers from the effects of atmospheric constituents and unfavourable weather conditions such as rainfall, fog and cloud cover; this problem restricts the application to opportune weather conditions (Belgiu & Dragu, 2016).
et al., 2018; Omar et al., 2017; Thapa et al., 2015; Ulrich et al., 2020). Although RADAR remote sensing provides a solution for all-weather biodiversity assessment, it is more effective in capturing structural variations than chemical and genetic compositions that are well characterised by optical data.

RADAR and optical images can be fused for biodiversity assessment purposes (Borges et al., 2020; Heckel et al., 2020; Slagter et al., 2020). The integration specifically exploits spectral information of optical data and structural metrics provided by RADAR to differentiate the characteristics of plant species types (Kulkarni & Rege, 2020). Data fusion of optical and RADAR images has shown improvement over single images (e.g. Ali et al., 2018; Attarchi & Gloaguen, 2018; Ienco et al., 2019; Jhonnerie et al., 2015; Slagter et al., 2020; Zhao et al., 2016). For instance, Kattenborn et al. (2015) classified different vegetation types using fused EO1-Hyperion, Tandem-X and WorldView-2 images reporting the best overall accuracy of 73%. Although the data sets used in that study are rich in spatial, structural and spectral information, they are not readily available for low-cost and routine applications. Mendes et al. (2019) recorded overall accuracy of 83% in classifying four woody plant species with distinct structure and composition: (i) Cerrado denso (height measuring up to 8 m and crown cover of 5–70%); (ii) Cerrado (height measuring up to 15 m and crown cover of 50–90%); (iii) gallery forest (height up to 30 m and crown cover of 70–95%); (iv) secondary forest (height up to 8 m and crown cover of 20–90%). Attarchi and Gloaguen (2018) classified six structurally distinct plant species with plant heights ranging between 6 and 35 m, and different leaf dimensions (ranging from 2 cm to 20 m). In this study, a combination of Landsat Enhanced Thematic Mapper (ETM) and Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar (ALOS PALSAR) was utilised reporting 87% overall accuracy. Their study separated only a few spectrally and structurally distinct plant species, and is expected to have been relatively simple.

Sentinel-1 C-band RADAR and Sentinel-2 multispectral datasets with moderate spatial and spectral resolutions can provide an ideal pair for accurate biodiversity assessment at no cost (e.g. Cai et al., 2019; Haas & Ban, 2017; Hajj et al., 2019; Kattenborn et al., 2019; Slagter et al., 2020; Talema & Hailu, 2020). This has been supplemented by the rapid growth in machine learning techniques, which yield improved classification capability. For example, Hirschmugl et al. (2018) fused Sentinel-1 C-band and Sentinel-2 and applied Random Forest (RF) classification to map different forest types, with fairly good overall accuracy (>69%). Clerici et al. (2017) fused Sentinel-1 and Sentinel-2 images and applied RF, Support Vector Machine and k-Nearest Neighbor classification recording overall accuracies ranging between 40–89% in classifying three distinct vegetation species and land cover types dominated by coniferous and deciduous forests. Fairly good accuracies reported in the aforementioned studies were attributed to significant differences in foliage morphology, chemical composition and structure of vegetation formations. Unlike similar morphologies amongst plant species, physiological variations that exist between different plant forms are easy to discriminate (Adhikari et al., 2020). It is therefore important to explore the application of non-commercial fused images with moderate spatial and spectral resolutions (such as those derived from Sentinel-1 C-band and Sentinel-2 multispectral data) in discriminating multiple plant species (n > 27) with morphologically similar characteristics (e.g. narrow-leaved woody plant species) in savanna environments.

The present study, therefore, aims to investigate the utility of fused Sentinel-1 C-band RADAR and Sentinel-2A optical data in discriminating morphologically similar woody plant species in a localised savanna environment using the Deep Neural Network (DNN) classification. DNN machine learning classification, an advanced multimodal data analysis technique, has the strength of learning abundant multi-scale features from optical and RADAR data. Successful findings from this study are envisaged to contribute to efficient biodiversity assessment, which is crucial for sustainable ecological management, particularly in species diversity hotspots within localised environments.

**Methods**

**Study area**

The present study was conducted in the Klipriviersberg Nature Reserve (NKR) located in Johannesburg, South Africa (Figure 1). The NKR, which covers 651 hectares, was declared as a conservation area in 1984. Altitude of the study area ranges from 1540 m in the southern part to 1790 m in the northern part, with the mean altitude at 1653 m. The mean annual rainfall of the area surrounding the reserve ranges from 624 to 802 mm (Kruger & Nxumalo, 2017). Mean daily temperature ranges between 17°C and 26°C in the rainy summer period and 5°C and 7°C in the dry winter period (MacKellar et al., 2014). The floristic structure of the reserve is influenced by the geology which includes quartizes, conglomerates and dolomites (Molezzi et al., 2019). Vegetation in the reserve is dominated by Andesite Mountain Bushveld and Clay Grassland (South African National Biodiversity Institute, 2012).
Field data

In this study, a grid of 240 points was distributed at roughly 170 m intervals in the north–south and east–west directions, which covered the whole study area. The points were generated in ArcGIS (ESRI® ArcGIS 10.6, Redlands, California, USA) and uploaded onto a Global Position System (GPS) (Garmin, GPSMAP® 64, Kansas, USA) and subsequently located in the field. A 20 m radius buffer was created around each point; this buffer size was preferred to include multiple pixels of the Sentinel data used in the study. In each plot, all woody plants with a height ≥2m and land cover types (shrubs, grassland and bareland) were counted. In each plot, a minimum of 1 plant species and maximum of 9 plant species were recorded, while a total of 27 distinct woody plant species were counted in all plots. Field surveys were done in November 2017, representing wet period (MacKellar et al., 2014).

Remote-sensing data and preprocessing

Sentinel-2A and Sentinel-1 C-band data acquired in November 2017 were downloaded from the European Space Agency Data Hub (https://scihub.copernicus.eu/dhus/). Sentinel-2A imagery has a total of 13 bands, covering the visible and infrared regions of the electromagnetic spectrum. This study omitted three bands, including coastal (0.43–0.45µm), water vapour (0.93–0.95 µm), and cirrus bands (1.36–1.39 µm) from the analysis, due to their sensitivity to atmospheric interferences (Stych et al., 2019). The remaining 10 bands (red, green and blue (RGB), near-infrared (NIR), vegetation red edge (VRE) and short-wave infrared (SWIR)) covered a wavelength range between 0.41 and 2.28 µm (Figure 2). A comparison of three atmospheric correction approaches including Dark Object Subtraction (DOS) (Chavez, 1996), Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLASH) (Adler-Golden et al., 1999) and Sen2Cor (Main-Knorn et al., 2017) showed strong similarity in the resultant spectral values (Pearson’s correlation, r > 0.98). The DOS, therefore, was implemented to all individual bands of the Sentinel-2A image. Subsequently, all the individual bands of the Sentinel-2A image were stacked to create a multispectral image.

Sentinel-1 C-band is retrieved in both single Horizontal–Horizontal (HH) or Vertical–Vertical (VV) polarisation and dual polarisations (HH+HV or VV+VH), implemented through one transmit chain switchable to H or V (Table 1) (Copernicus, 2014). For this study, VH, VV, VH+VV and ratio of VH/VV polarisations were used. The data was downloaded as a Level-1 Ground Range Detected (GRD) product, which had already been preprocessed using multi-looking and projection to ground range using an Earth ellipsoid model (Copernicus, 2014). The spatial resolution of the dataset is measured at 10 m, which is believed in this study to be a moderate/fine resolution for localised species diversity estimation (Axelsson & Hanan, 2017).
Figure 3 summarises the preprocessing applied to the data and the analysis followed in the study. The preprocessing started with the radiometric calibration of the RADAR image, in order to convert the digital number value of each pixel (i) to a sigma naught backscatter value, using Equation 1. The calibration considers the local incidence angle and thus takes into account local topographic conditions of the area of interest (Copernicus, 2014). This was done to provide an image in which pixel values can be directly related to the RADAR backscattering of species and coexisting land cover types (Equation 2) (Van Tricht et al., 2018).

\[
\text{Value}(i) = \frac{|DN_i|^2}{A_i^2} 
\]

(1)

Pixel value (i) = original DN, and Ai = sigma nought (i)

\[
\sigma_\text{db}^0 = 10 \log_{10} \sigma^0
\]

(2)

where \(\sigma_\text{db}^0\) = backscattering coefficient in decibels

After applying radiometric calibration, speckle filtering was carried out to improve the quality of the image by reducing the salt-and-pepper appearance that is common in RADAR data (Zhu et al., 2018). This study applied the widely used Lee-Sigma filter (Lee, 1983), which utilises the statistical distribution of the Digital Numbers (DN) values within a moving kernel, to estimate the value of the pixel of interest in the image data. The Lee-Sigma filter replaces the pixel of interest with the average DN values of pixels within the moving kernel. Three different window sizes (3 × 3, 5 × 5, and 7 × 7) were tested for this study, with 7 × 7

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**Table 1. Characteristics of Sentinel-1 C-band that was used in this study.**

| Characteristic          | Value                        |
|-------------------------|------------------------------|
| Incidence angle range   | 29–46°                       |
| Swath width             | 250km                        |
| Spatial resolution      | 10m                          |
| Polarisation options    | VH, W, VHV and VH/VV         |
| Radiometric accuracy    | 1dB (3σ)                     |

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Figure 2. Spectral regions of Sentinel-2A image used in the study.

Figure 3. Flowchart representing the methodological approach adopted for the present study.
window size yielding the best output, based on visual inspection of the image. These observations agree with Dasari and Anjaneyulu (2017) who postulated that as the speckle filter window size increases, speckles in an image decrease, resulting in smoothed edges. Speckle filtering is applied to smooth the speckle noise inherent in RADAR data and retain the edge as well as feature boundary sharpness on the image (Lee et al., 1994; Saxena & Rathore, 2013). The last stage in preprocessing was terrain correction (Figure 3) using Range-Doppler to compensate for distortions caused by topographic variations and tilt of the satellite sensor (Braun, 2020; Figure 3). Veloso et al. (2017) and Vreugdenhil et al. (2018) applied a RADAR image in the classification of vegetation, and reported high explanatory power of combining single polarisation with the ratio of single polarisations, which compensate for the backscatter characteristics or radiometric instability of the sensor. Thus, our study computed VH + VV polarisations and ratio of VH/VV polarisations as additional bands for classification of plant species with morphologically similar characteristics. The above preprocessing steps were implemented in Sentinel Application Platform (SNAP) software provided by the European Space Agency (ESA) (http://step.esa.int/main/download/snap-download/).

**Data fusion**

Combinations of optical and RADAR data have been shown to perform better than the use of a single sensor in the classification of plant species (Astola et al., 2019; Bartsch et al., 2020). This study utilised Principal Component Analysis (PCA) to combine Sentinel-1 and Sentinel-2 bands. The PCA is a statistical tool that transforms multiple data having correlated variables into condensed data sets each, containing unique information (Chavez & Kwarteng, 1989). Specifically, the PCA (Equation 3) was applied to the Sentinel-2 to generate principal components (PCs). The multispectral bands which produced the least amount of information in the PCs were replaced with Sentinel-1 C-band data including VH, VV, VH + VV, and the ratio VH/VV bands. An inverse principal component transform which converts principal component layers back to image space (He & Yokoya, 2018) was then applied to fuse the dataset. The resultant fused image contained four polarisations of Sentinel-1 C-band as well as eight multispectral bands of Sentinel-2A, resulting in a fused image with 12 bands. The fused image was then used for the classification of 27 woody plant species and three coexisting land cover types.

\[
\text{PCA} = (C - \lambda_k I) W_k \tag{3}
\]

where C is the covariance matrix, \(\lambda_k\) is the k eigenvalues, I is the diagonal identity matrix and \(W_k\) is the k eigen vectors.

**Training and classification of remotely sensed data**

Training of the classes was performed on the Sentinel-1 C-band, Sentinel-2A and the fused images separately. A total of \(n = 8080\) points representing 27 woody plant species as well as grass, shrubs and bareland were digitised inside the 240 plots on the three images. Digitising of points was guided by field surveys in which a local cartesian coordinate system was used to locate the species. Finally, points were split into two sets: training and validation. We compared three data splitting sizes including 20 versus 80, 25 versus 75 and 30 versus 70% for training and validation purposes, respectively. The results did not show significant variation and therefore we opted for the 30% \((n = 2441)\) 70% \((n = 5639)\) data split. We believe that using a smaller portion of the samples for training reduces model overfitting that would have resulted by training the entire sample set. The spatial distribution of the training samples was taken into consideration when splitting the data into training and evaluation sets. The species, along with the proportions allocated to the training and testing of the classifications, are given in Table 2.

**Deep neural network classification**

The study used Deep Learning (DL) classification that is capable of learning a high- and low-level constructs of data better than conventional machine learning algorithms (Beyesolow, 2017). DNN was selected for this study because of its capacity to generate non-linear decision boundaries and thus it can identify complex patterns (Lavine & Blank, 2009). Specifically, DNN with error backpropagation was applied using the H20 package in R language (Darren, 2016). The algorithm uses multi-layer perceptrons that consist of multiple layers (Figure 4): (i) an input layer which contains one or more processing elements; (ii) hidden layers that are responsible for the transformation of data between input and output layers; and (iii) an output layer which stores the results of the network (Mousavi et al., 2018). Illustration of the DNN architecture is shown in Figure 4. In order to compute class probabilities, this study used an output activation function known as hyperbolic tangent (tanh) with a softmax output classification (Ma et al., 2019). Tanh function yields zero-centred outputs and enables frequent update on model parameters in a feed-forward neural networks (Lavine & Blank, 2009). Classification of the three images (Sentinel-1 C-band, Sentinel-2A and the fused image) was performed separately using 30% of the data \((n = 2441)\) samples. Activation, hidden layers, neurons per layer and epochs hyperparameters were
Table 2. Illustration of the number of woody plant species used for training and evaluation of classification.

| Species Name          | Code | Leaf Structure | Training | Classification | Validation |
|-----------------------|------|----------------|----------|----------------|------------|
| Accacia caffra        | AC   | Narrow-leaved  | 265      | 637            |            |
| Accacia delavata      | AD   | Narrow-leaved  | 48       | 208            |            |
| Accacia karro         | AK   | Narrow-leaved  | 177      | 252            |            |
| Afrotamnium           | AM   | Narrow-leaved  | 120      | 160            |            |
| Brachylaena           | BR   | Narrow-leaved  | 104      | 172            |            |
| Celtis africana       | CAf  | Narrow-leaved  | 62       | 139            |            |
| Celtis australis      | CAu  | Narrow-leaved  | 62       | 124            |            |
| Cordyline             | CO   | Narrow-leaved  | 135      | 262            |            |
| Disyros               | DN   | Broad-leaved   | 50       | 284            |            |
| Dombeya               | DR   | Broad-leaved   | 72       | 168            |            |
| Ehretia rigida        | ER   | Narrow-leaved  | 110      | 214            |            |
| Euclea crispa         | EC   | Narrow-leaved  | 75       | 138            |            |
| Gymnosporia           | GB   | Narrow-leaved  | 50       | 245            |            |
| Heteromorpha          | HA   | Narrow-leaved  | 38       | 155            |            |
| Kigelia africana      | KA   | Narrow-leaved  | 88       | 176            |            |
| Melia azedarach       | MA   | Narrow-leaved  | 79       | 105            |            |
| Olea europaea         | OEa  | Narrow-leaved  | 66       | 175            |            |
| subafricana           |      |                |          |                |            |
| Pittosporum           | PV   | Narrow-leaved  | 62       | 152            |            |
| Populus x canescens   | PC   | Broad-leaved   | 40       | 153            |            |
| Rhus lancia           | RL   | Narrow-leaved  | 59       | 141            |            |
| Salix mucronate       | SM   | Narrow-leaved  | 104      | 151            |            |
| Sambucus nigra        | SN   | Narrow-leaved  | 48       | 168            |            |
| Searsia               | SL   | Narrow-leaved  | 77       | 126            |            |
| leptodictya           |      |                |          |                |            |
| Searsia pyrodes       | SP   | Narrow-leaved  | 67       | 157            |            |
| Tarchonanthus         | TC   | Narrow-leaved  | 71       | 105            |            |
| Zanthoxylum           | ZC   | Narrow-leaved  | 45       | 114            |            |
| mucronate             |      |                |          |                |            |
| Bareland              | BL   | No leaf        | 54       | 279            |            |
| Grassland             | GL   | No leaf        | 73       | 133            |            |
| Shrubbs               | SH   | Mixed          | 60       | 152            |            |
| TOTAL                 |      |                | 2441     | 5639           |            |

optimised using a grid search approach. A ten-fold cross-validation repeated 10 times was used to determine the best possible combinations of the hyperparameters.

Accuracy assessment

Classification accuracies derived from the remotely sensed data were assessed on the 70% test dataset (n = 5639) of the woody plant species and coexisting land cover types in Google Earth Engine. An error matrix that uses overall, producer’s and user’s accuracies (Congalton & Green, 2009) were used in the study. Overall accuracy is the probability that an individual class will be correctly classified. It is measured by the summation of the true observations plus predicted observations, divided by the total number of tested classes. The producer’s accuracy shows the likelihood of a reference class being correctly classified, and it is calculated as the number of true observations of a particular class divided by the number of true reference observations of that class. The user’s accuracy is calculated as the number of true observations of a particular class divided by the number of predicted individuals of that class. A kappa coefficient (Equation 4) was also used to assess the quality of classified imagery (Story & Congalton, 1986). The statistical measure is used to control the instances, which might have been correctly classified by chance.

Kappa coefficient = \( \frac{P_{\text{observed}} - P_{\text{chance}}}{1 - P_{\text{chance}}} \) (4)

where \( P_{\text{observed}} \) = observed proportion of agreement and \( P_{\text{chance}} \) = proportion expected by chance.

The McNemar’s test (McNemar, 1947) was employed in the study to determine if there were statistically significant differences between various classification scenarios (i.e. optical vs. RADAR, optical vs. fused image and RADAR vs. fused image). This test was implemented using Equation 5.

\[ Z = \frac{|12 - 21|}{\sqrt{12 + 21}} \] (5)

where the square of z follows a chi-square \( \chi^2 \) distribution with 1 degree of freedom. \( f_{12} \) represents the misclassified number of samples using, for example, optical image but classified correctly by a different image (e.g. RADAR). \( f_{21} \) represents total number of samples classified correctly by a classifier using optical image and not classified by RADAR images. The pairwise comparison was implemented for overall accuracies as well as for species-level accuracies.

Results

Classification accuracies using Sentinel-2A, Sentinel-1 C-band and fused image

Figure 5 shows visual comparisons of classes according to Sentinel-2A, Sentinel-1 C-band and fusion of the two images. The classification output, representing 27 woody plant species and three coexisting land cover types (Table 2) identified in the study area. A look at a select places highlighted using circles and ellipses illustrate differences in the performances of the three data types. Overall classification accuracies of species and coexisting land cover types derived from the three images showed that the fused image achieved the highest overall accuracy of 76%, followed by Sentinel-2A (72%) and then Sentinel-1 C-band (71%) (Figure 6). The kappa coefficient statistics retained the same ranking order as the overall accuracies, with the fused image recording the highest kappa coefficient value of 0.73, followed by Sentinel-2A (0.68) and Sentinel-1 C-band (0.64) (Figure 6). The difference in the accuracies, displayed from both the overall accuracies...
and kappa coefficient values, showed that the fused image performed better compared to the two individual images (Sentinel-2A and Sentinel-1 C-band).

Results from the McNemar’s test showed that pairings of all images had statistically significant different outputs with $\chi^2 = 7.35$ ($p = 0.003$) for fused image

Figure 4. DNN architecture with two hidden layers, each layer consists of multiple neurons, which are fully connected with neurons of the previous and following layers. Figure 4 needs to be corrected to Figure 4

Figure 5. Visual illustration on the performances of Sentinel-1 C-band (a), Sentinel-2A (b) and fusion of the two images (c) in classifying woody plant species and coexisting land cover types.
versus Sentinel-1 C-band, $\chi^2 = 6.44$ ($p = 0.007$) for fused image vs. Sentinel-2A and ($\chi^2 = 4.58; (p = 0.023$) for Sentinel-1 C-band versus Sentinel-1 C-band. Producer’s and user’s accuracies of individual plant species and coexisting land cover types are shown in Figure 7. A closer look at the producer’s accuracies from the three images shows that high accuracies were recorded from the fused image, where the values ranged between 48% and 94% for different species and coexisting land cover types. The fused image produced accuracies exceeding 75% for 15 species and coexisting land cover types, and accuracies >85% for three species (Figure 7a). The producer’s accuracies ranged between 42% and 91% for different plant species using the Sentinel-2A image (Figure 7a). When using Sentinel-2A imagery, 13 species and coexisting land cover types had producer’s accuracies exceeding 75%, with four of them having 85% or higher accuracies. Slightly lower producer’s accuracies were recorded from the Sentinel-1 C-band alone, with the values ranging between 35% and 89% for different plant species. This imagery yielded producer’s accuracies greater than 75% for 13 species and coexisting land cover types, while the accuracies exceeded 85% for two species. Focusing on user’s accuracies (Figure 7b), the three images (Sentinel-2A, Sentinel-1 C-band and fused image) yielded accuracies ranging between 36% and 96%. The user’s accuracies using Sentinel-2A imagery (ranged between 36% and 96%) recorded >75% for nine species and >85% for four species and coexisting land cover types. Although the accuracies using Sentinel-1 C-band ranged between 44% and 89%, 11 species and coexisting land cover types had accuracies greater than 75% and two species >85%. In contrast, the fused image yielded accuracies ranging between 40% and 96%, with 12 species and coexisting land cover types having accuracies greater than 75% and six species >85% (Figure 7b).

Performance of the three images (Sentinel-2A, Sentinel-1 C-band, fused image) in correctly identifying species and coexisting land cover types was compared using the producer’s accuracy. The producer’s accuracy was selected for this analysis because it indicates the likelihood of a species in the reference data being classified correctly. The fused image was better than the sole use of Sentinel-2A for 16 species and coexisting land cover types (Figure 8a) with the improvement in producer’s accuracy ranging between 1 and 35 percentage points. The improvements exceeded 10% for seven species and 20% for two species. Similarly, the fused image was better than the sole use of Sentinel-1 C-band for 16 species and coexisting land cover types, with the improvement ranging between 1% and 42% (Figure 8a). Of these, the improvements over Sentinel-1 C-band exceeded 10% for 12 species and 20% for six species. Figure 8b shows that Sentinel-2A was better than Sentinel-1 C-band for 16 species and coexisting land cover types, with improvements ranging between 1 and 48 percentage points. This improvement exceeded 10% for nine species and 20% for six species. The improvement of Sentinel-2A over the fused image was observed for eight species, with the improvements ranging between 1 and 29 percentage points (Figure 8b). It is also important to note the improvement of Sentinel-1 C-band over the other two, although it showed less improvements than the other two had over it. Specifically, Sentinel-1 C-band was better than Sentinel-2A for 11 species, with improvements ranging between 1% and 47% (Figure 8c). This improvement exceeded 10% for eight species and 20% for three species. Sentinel-1 C-band’s improvement over the fused image was noted for 11 species (Figure 8c), and improvements ranged between 1 and 18 percentage points. Sentinel-1 C-band’s superiority over the fused image exceeded 10% for seven species and coexisting land cover types (Figure 8c).

**Species confusion levels of Sentinel-2A, Sentinel-1 C-band and the fused image**

Confusion of a species with a number of other unique species and land cover types was computed for the three images (Sentinel-2A, Sentinel-1 C-band and fused image), in order to establish which image would produce the least confusion in a species hotspot set-up represented by the study area (supplementary materials Table S1). Figure 9 provides the count of species and land cover types against which a species is confused. A low number of species confusion was recorded from the fused image,
showing its superiority to Sentinel-2A and Sentinel-1 C-band images. On average, a species was confused with eight other species when using the fused image, with 16 species having been confused with less than the average number (Figure 9). *Heteromorpha arborescens* was confused the most number of times \((n = 19)\) with other unique species, whilst *Brachylaena rotundata* was the least confused species \((n = 2)\) with unique species and land cover types. The Sentinel-2A image resulted in a classification in which a species was on average confused with 10 unique species, while 14 species were confused with less than the average number. *H. arborescens* was confused the most with other species \((n = 20)\), while *B. rotundata* was confused the least number with other species \((n = 3)\). On average, a species was confused with 12 other species using Sentinel-1 C-band, with 14 species having been confused with less than the average number. Using Sentinel-1 C-band imagery, grassland, *Sambucus nigra* and *Searsia leptodictya* were each confused with the most number of unique species \((n = 20)\), while *Dispyros natalensis* was confused with the fewest number of other unique species and land cover types \((n = 5)\) (Figure 9).

**Variable importance of optical and RADAR data**

Variable importance is calculated by the sum of the relative decrease in error when any variable is removed from the classification process (Kuhn, 2008; L. Ma

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**Figure 7.** Accuracies of identifying individual species using Sentinel-2A, Sentinel-1 C-band and fused image producer’s accuracy (a) and user’s accuracy (b). Species names represented by the two-or three-letter codes are given in Table 2.

**Figure 8.** Relative producer’s accuracy of an image over the other images in identifying each species type. Sentinel-2A, Sentinel-1 C-band and the fused image in the y-axes represent satellite images. Species names represented by the two-or three-letter codes are given in Table 2.
et al., 2019). Variable importance was computed in order to observe a general trend in terms of individual band importance (Figure 10). Overall, relative contribution of Sentinel-2A multispectral bands to the classification averaged around 6.8%. In contrast, the three polarisations and the derived index of polarisation (VH/VV) from the Sentinel-1 C-band had an average contribution of 7.9%, with the single polarisations having lower contributions. A closer look at individual band contributions shows that the near-infrared had the highest contribution (9.86%) in classifying unique species and land cover types, followed closely by SWIR1 (9.52%), while SWIR2 had a significantly lower contribution of 7.8%. The average contribution of VRE bands to the classification was 7.7%, with the VRE4 recording the highest contribution (8.3%), while the VRE2 recorded the least contribution of 7.2% (Figure 10). Looking at the RADAR, each of the polarised images contributed to greater than 7% of classifying the woody plant species and coexisting land cover types. The derived index of polarisation (VH/VV) recorded the highest contribution of 76%, followed by the double polarisation of VH+VV (8.6%). Amongst the single polarisations, VH recorded a contribution of 7.8%, which was slightly higher than VV with 7.2%, in the classification of unique species and coexisting land cover types (Figure 10).

Discussion

Performance of Sentinel-2A, Sentinel-1 C-band and fused image

This study investigated the utility of Sentinel-2A and Sentinel-1 C-band and the fused image, in classifying multiple woody plant species with morphologically similar characteristics. Sentinel-2A produced a marginally better overall accuracy than Sentinel-1 C-band (Figures 5, 6 and 7b). Similar good performances of Sentinel-2A were reported by Castillo-Riffart et al. (2017), Attarchi and Gloaguen (2018), Persson et al. (2018), Wang et al. (2018), and Chrysafis et al. (2019), and Cross et al. (2019) for species diversity classification in different vegetation environments. It is important to evaluate classification accuracy against spatial resolution of image, with smaller pixel sizes (high resolution) being preferred to reduce the probability of a mixed pixel scenario (Augustine et al., 2019). In light of this, the accuracies achieved in our study using 10 m resolution image can be considered encouraging. This success can be attributed to the image’s improved spectral properties such as having multiple bands particularly within the vegetation-sensitive region of the electromagnetic spectrum (Abdi, 2020). In addition, the variation in nutrient concentrations due to high biochemical activities
during wet season can contribute to high species discrimination accuracies using spectral information (Wei et al., 2020). During the wet period, chloroplasts degrade, releasing foliar nutrients like leaf protein and chlorophyll pigments, which interact with radiation captured by the multispectral image (Gara et al., 2019).

The combination of Sentinel-2A and Sentinel-1 C-band improved the accuracies of classifying woody plant species in the present study, compared to the sole use of Sentinel-2A and Sentinel-1 C-band images (Figure 6 and 8). This finding agrees with Lopes et al. (2020), who classified different plant species and reported better performance using fused optical RADAR than individual images. The study by Lopes et al. (2020) focussed on an environment characterised by more spectrally distinct vegetation forms than our study; we therefore consider our result encouraging for mapping species in biodiversity-rich environments. The study by Ali et al. (2018) using a combination of Landsat image and ALOS PALSAR RADAR image reported a better classification accuracy than our study; however, that study considered fewer species and land cover types than ours ($n = 6$ versus $n = 30$). The improvement in the producer’s accuracies of many of the species, in addition to the overall accuracy, using the fused image (Figure 7) strengthens the case for data fusion. This success is further corroborated by the lower confusion levels in identifying each species when compared to the confusion observed by the sole use of Sentinel-2A and Sentinel-1 C-band images (Figure 7). One source of confusion when using RADAR data can be due to the similarity of structural attributes between different species. This confusion is mitigated by the spectral properties of the species obtained from optical image on fused image (Bartsch et al., 2020). Similarly, RADAR data aids in discriminating species types with distinct physiological metrics even if the species exhibit comparable spectral properties. In contrast, Sentinel-2A fails to differentiate spectrally similar species. Furthermore, RADAR backscatter variation in response to plant water content variation among species adds information to the classification and thus allows for improved biodiversity mapping (Chuvieco & Huete, 2009; Kulkarni & Rege, 2020; Parrens et al., 2019; Zhang et al., 2019).

Uncertainty and potential for improvements

The moderate spatial resolution (10 m) of Sentinel used in the present study can be affected by mixed pixel problems (Karlson & Ostwald, 2016), particularly when multiple species occur in a localised area. To overcome this limitation, a study by Abdikan et al. (2015) fused high-resolution RapidEye (5 m) and TerraSAR-X (8 m) to discriminate between different vegetation types and land cover, achieving a high accuracy (95%). This indicates the importance of improving the spatial resolution of Sentinel-2A, which already has improved spectral qualities, especially in the vegetation-sensitive regions of the electromagnetic energy. Another solution can involve spectral unmixing (spectral mixture analysis) that decomposes information within a pixel by using spectra of individual species within that pixel (Huang et al., 2010). However, implementing spectral decomposition of pixels requires pure spectral signatures of individual species that were not available in our study. Polarimetric decomposition, which utilises the phase information of a radar signal can also improve the classification results, by enhancing the identification of different scattering mechanisms of the plant species (Harfenmeister et al., 2021). Although Sentinel-1 C-band returned the lowest accuracies, the overall accuracy of 71% coupled with the fact that the image is an active microwave system that can be applied in all-weather conditions is reassuring (Bartsch et al., 2020). However, it is important to note the better improvement of Sentinel-2A over Sentinel-1 C-band rather than the opposite for most species (Figure 8b). This can be explained by the fact that physiologically similar species may not be differentiated by RADAR data (Heckel et al., 2020). Furthermore, C-band RADAR is strongly attenuated by vegetation canopies, causing scattering intensities to be similar for plant types with subtle structural differences (Ienco et al., 2019; Naïdoo et al., 2015; Slager et al., 2020). In such a case, the spectral response of plants can become more valuable in discriminating species (GANivet & Bloomberg, 2019).

It is crucial to expect a suboptimal classification capability of one-time data if a given area hosts plant species that show significant seasonal variations (El Mendili et al., 2020; Wakulinska & Marcinkowska-Ochyra, 2020). In addition, phenological cycles affect biochemical concentrations in plants and therefore the classification accuracy can vary with time (Fu et al., 2021; Wu et al., 2021). Adoption of multi-temporal analysis can therefore improve the performance of fused Sentinel datasets with high temporal resolution, compared to relying on single date analysis utilised in our study.

Conclusions

The present study assessed the performances of Sentinel-1 C-band and Sentinel-2A images, and a fusion of the two images to detect several plant species with similar morphological characteristics in a savanna environment. The fused image performed better with higher overall classification accuracy and lower confusion levels among species compared to the sole use of Sentinel-2A and Sentinel-1 C-band images. The findings highlighted the effectiveness of data integration in detecting woody plant species with similar (narrow-leaf) characteristics. Another positive attribute of the dataset utilised in this study is that both RADAR and optical (Sentinel products) are non-commercial, with large spatial extents and high temporal resolutions that allow for short-diurnal monitoring of wide spatial
extends. While the results of this study are promising, it is important to acknowledge the need for non-commercial images with improved spatial (sub-10 m) and spectral resolutions (>10 bands), for detailed biodiversity assessments and species diversity monitoring strategies. This study also recommends further exploration on the use of multi-temporal data to capture changes in vegetation characteristics with time, particularly in areas where species diversity is high.

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Data availability
The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials (Table S1).

Disclosure statement
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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