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Identification of Commercial Forest Tree Species Using Sentinel 2 and Planet Scope Imageries in the Usutu Forest, Eswatini

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Abstract

Making the distinction between different plantation tree species is crucial for creating reliable and trustworthy information, which is critical in forestry administration and upkeep. Over the years, forest delineation and mapping have been done using the conventional techniques, such as the utilization of ground truth facts together with orthophotos. These techniques have been proven to be very precise, but they are expensive, cumbersome, and challenging to employ in remote regions. To resolve this shortfall, this research investigates the potential of data from the commercial, PlanetScope CubeSat and the freely available, Sentinel 2 data from Copernicus to discriminate commercial forest tree species in the Usutu Forest, Eswatini. Two approaches for image classification, Random Forest (RF) and the Support Vector Machine (SVM) were investigated at different levels of the forest database classification which is the genus (family of tree species) and species levels. The result of the study indicates that, the Sentinel 2 images had the highest species classification accuracy compared to the PlanetScope image. Both classification methods achieved a 94% maximum OA and 0.90 kappa value at the genus level with the Sentinel 2 imagery. At the species level, the Sentinel 2 imagery again showed highly acceptable results with the SVM method, with an OA of 82%. The PlanetScope images performed badly with less than 64% OA for both RF and SVM at the genus level and poorer at the species level with a low OA figure, 47% and 53% for the SVM and RF respectively. Our results suggest that the freely available Sentinel 2 data together with the SVM method has a high potential for identifying differences between commercial tree species than the PlanetScope. The study uncovered that both classification methods are highly capable of classifying species under the gum genus group (*esmi*, *egxu*, and *egxn*) using both imageries. However, it was difficult to separate species types under the pine genus group, particularly discriminating the hybrid species such as *pech* and *pell* since *pech* is a hybrid species for *pell*.

Keywords

Sentinel-2, PlanetScope, Random Forest, Support Vector Machine, Sugarcane, Genus, Species, Remote Sensing

1. Introduction

Eswatini has a sizable forestry industry that occupies close to a million hectares, or forty five percent of Eswatini's overall area [1] [2]. 14 percent of this land is covered by cultivated plantations, while about 86 percent of it is covered by wild forests and woodlands. Commercial forestry and related businesses play a significant role in Eswatini's economy, providing about 1.3 percent to the GDP and 1.4 percent of all exports in recent years [3]. According to the [4] report, over 8000 people are employed in the forestry and forest products (wood processing) sectors, which account for 14 percent of all official employment in Eswatini. As a result, it is very imperative that the dispensation of the forest types is monitored for accurate production estimates.

These commercial forest plantations' economic worth and ecosystem functions are highly reliant on the diversity of their tree species [5]. Therefore, details about the dispersion, composition, and productivity of commercial tree types are essential in managing and monitoring commercial forests because several types of woodland trees are regularly impacted by numerous risks, like insects, plant pathogens, wildfire risk, procedures for handling, and felling timing [6]. To this end, it is essential to produce precise and current species distribution maps, particularly at a localized size, in order to apply knowledgeable management techniques and policies. Due to the lack of standardized assessment and monitoring methods, technical and scientific skills, plantation tree type classification and locating continue to be a difficult task in Southern Africa [7] [8]. Therefore, practical as well as economical spatial methods and databases for forest species mapping must be developed.

Over the past decades, forest delineation and mapping have been done using conventional techniques, such as the utilization of ground truth facts together with orthophotos. Even though these techniques have been proven to be very precise, they are expensive, cumbersome, and challenging to employ in remote regions [9] [10]. Lately, the integration of field observation and remote sensing techniques has proven effective in delivering the trustworthy data required for forest species mapping [11]-[14]. In order to map and differentiate between current tree types, satellite-based sensor technologies can quickly and cheaply gather the information needed. As a result, there is a growing interest in using satellite-based sensor technologies within industrial plantations [7] [15] [16]. Along with machine learning techniques like Support Vector Machine (SVM) and Random Forest (RF), which have also shown efficacy in classifying different types of land cover, Sentinel-2 (S2) satellite imagery [17] [18] and PlanetScope imagery [19] have emerged as valuable resources for forest management and species identification.

According to some studies, imageries from Sentinel 2 have superior pixel size and wavelength intervals with additional bands put with greater care at the red edge [20]-[22]. Sentinel 2 interval data spanning the three seasons of the year were evaluated for their efficiency in mapping different types of forest trees by [16]. They discovered that the most accurate mapping was achieved with spring images and the autumn images. The research by [16] demonstrates that the assumed high accuracy level (90% OA) was exceeded by using just two images from two different seasons. [23] mapped invasive Australian acacia trees in KwaZulu Natal using S-2 multiple-time series based optimal characteristics with a fixed time interval. Their investigation demonstrated the significance of S-2 additional bands put with greater care at the red edge, in addition to the near infrared and short-wave infrared bands, for modelling and mapping the distribution of wattle trees from the satellite data.

The accessibility to finer pixel size data and more frequent sensor cycles have significantly assisted species mapping. For example, [24] categorized 5 types of trees in central Sweden using the unrestricted Sentinel 2 data and got 88.2% OA. A little later, using S-2 data, [25] correctly identified four different types of trees in southern Sweden with 87% OA. Recently, species-based studies have increasingly used data from multi-spectral sensors with finer pixel sizes (less than 5 m) obtained by profit making companies, e.g. PlanetScope, RapidEye, QuickBird and Worldview [26]. High temporal (daily) resolution PlanetScope data have significant benefits for capturing high-quality images for mapping forest species. Numerous earlier research has proven the capabilities of PlanetScope in species mapping e.g. [27] [28].

Separately, numerous research studies have utilized PlanetScope data for mapping structural data and forest cover, for example, [7] [29]. Around South Africa's KwaZulu-Natal (KZN) area, for instance, [7] examined the effectiveness and accuracy of different satellite data (RE, PS, Landsat-8 and S-2) in the classification of tree species diversity. By contrasting predictions generated with data from Landsat-8 and S-2, [29] examined the ability to predict tree crowns using PS and LiDAR data, and they demonstrated that RF models' prediction of canopy height was enhanced by the LIDAR data. With a rRMSE of 51.3% and an R2 of 0.70, PS data was sufficient for modelling at a three meter pixel size; but for large pixel or less detail sizes above 10 meters, RF methods employing S-2 imagery scored higher.

[30] used PlanetScope and Sentinel-2 Erspaceborne sensors to map striga weed using the random classifier and they concluded that, using the S2 chosen bands (B4, B3, B2, B8, and atmospherically resistant vegetation index), it was possible to detect the presence of striga in maize fields with 87% OA and 0.82 kappa value. Compared to those produced using PS, the findings were marginally lower (−5% deviance). The findings demonstrated that the bands chosen by PS (B3, B2, B1, atmospherically resistant vegetation index, and infrared percentage vegetation

index) yielded marginally better Landuse classification outcomes with 92% OA and 0.89 kappa value. It has been demonstrated that it is feasible to match and even outperform the imagery's overall predication precision by using a small number of well selected effective bands [31]. Moreover, this lessens the repetition caused by connected variables. Without sacrificing important details important to the features, the GRRF technique reduces multidimensional nature of the satellite data [32] [33].

In a region in northwest Morocco, [34] evaluated the effectiveness of 3 optic remotely sensed data for mapping. Between 2020 and 2021, satellite imageries (Landsat 8/LDCM, S-2, and PS) were used in a supervised classification method that employed the random forest algorithm. Their findings imply that classification accuracy increases in more detailed images with high frequency of satellite revisit. Compared to Landsat 8/LDCM and S-2 data, PS performed well with greater than 97% OA. Unfortunately, the prediction for PS alone was not much improved by the addition of the other 3 satellite data. Using every characteristic for PS and S-2, it is possible to precisely map pine trees. [19] investigated the effects of pixel size and features in the Italian mountains (Sarntal Valley) and got 90.95% OA for PS and 90.65% for S-2. Although having a lesser spatial resolution, Sentinel-2 can generally produce results that are comparable with PS with disregard to the image characteristics. In particular, adding textural features made minor improvements to the image classification results, plus eight percent for PS and three percent for S-2, although topographic features and canopy height only showed modest accuracy gains [19].

Even though many of S2 and PS's capabilities own a positive track record, such as farmland rating [17] [35], biofuel estimation [22], mapping aquatic plants [36] as well as understanding plant growth [37] [38], there is no evidence to support its use in identifying and classifying forest species in Eswatini that are used for commercial purpose. Most of the studies that have already been done have concentrated in other locations, mostly outside Africa, frequently ignoring the unique environmental conditions and landscape, and the difficulties faced by the forest industry of Eswatini. Therefore, this study seeks to address these gaps by evaluating the effectiveness of Sentinel-2 and PlanetScope imageries, together with machine learning techniques for identifying the different species found in the Usuthu Forest, Eswatini. The primary objectives are (1) To map homogenous forest stands comprising three different genus groups namely Acacia, Eucalyptus, and Pines in the Usuthu Forest using remote sensing, (2) To compare the usefulness of Sentinel-2 and PlanetScope data for mapping of commercial plantation tree species (3) Compare the performance of SVM and RF classifiers to the overall classification accuracy.

2. Materials and Methods

2.1. Study Area

This research was conducted within the Usutu Forest Plantations, Eswatini

(26˚27'32.1"S; 31˚01'50.8"E) (**Figure 1**). The forest plantations occupy the mountainous wet western part of the country (Highveld) covering about 78,000 hectares of land. With a slope of 4 to 56 degrees and an elevation range of 634 to 1662 meters above sea level, the region has climates that range from dry to humid with contrasting dry, frigid winters and hot, humid summers with sporadic frost. The average amount of annual precipitation fluctuates greatly from year to year and is roughly 1500 mm [39]. With some localized fluctuations brought on by physical factors, the yearly average temperature of around 21˚C is conducive, facilitating the establishment of varieties of trees in subtropical climates.

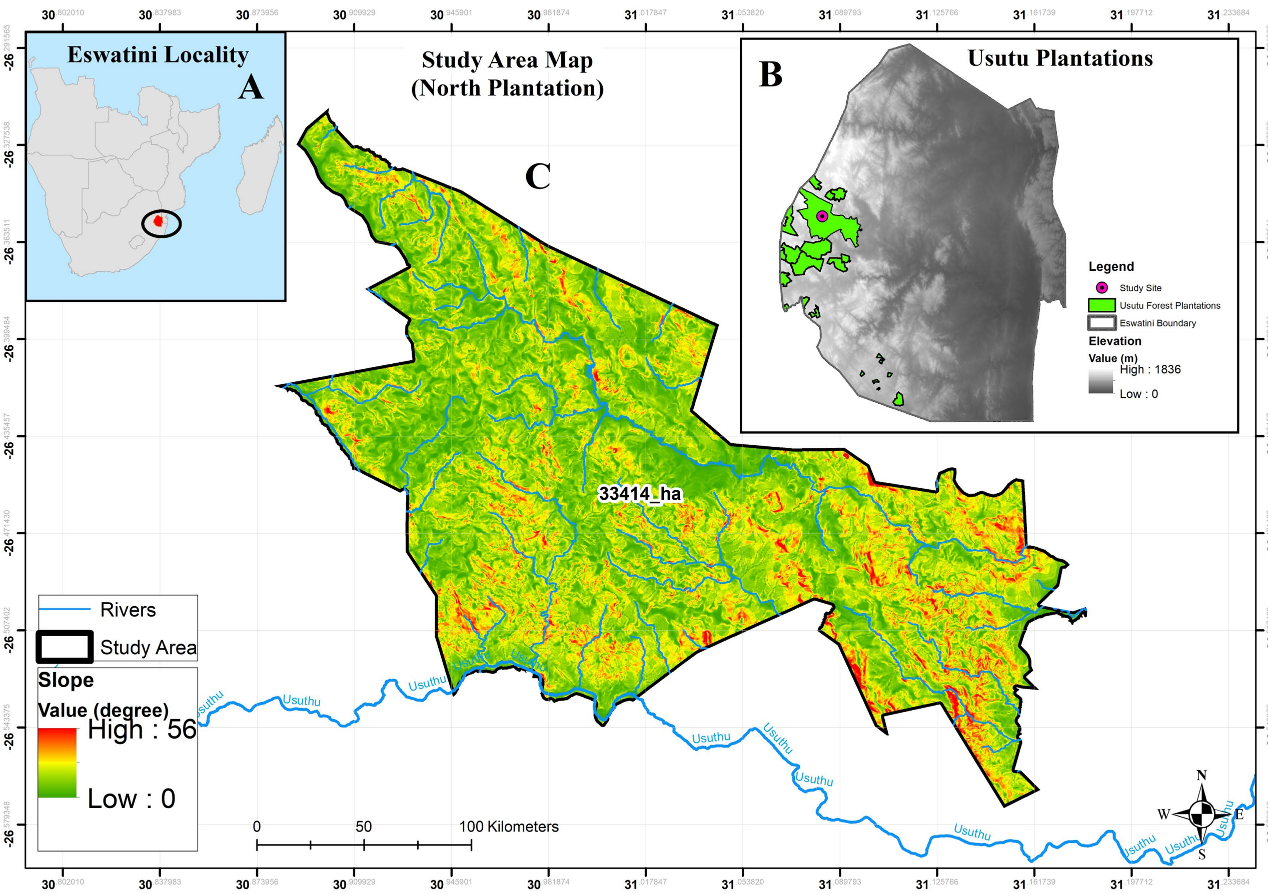


Figure 1. Study site Map. (A): Locality of Eswatini within the Southern African region. (B): Locality of the Usuthu Forest Plantations within Eswatini with a place mark within the study area. (C): Study area map (North plantation) showing the slope of the area and the rivers flowing through.

In the entire Usutu Forest plantation, about 60% of the area is planted with *Pine*, *Gum* is covering 23% of the area followed by *Wattle* at 19%. Area under Agriculture (Maize, Zea, etc.) and other oils are very insignificant. A location for the study site (block of compartments) which includes a variety of trees, spanning an area of 33,414 ha (**Figure 1(C)**) was chosen. The area was chosen because it is dominated by all the tree species types that were used in this research hence providing an opportunity to evaluate how well PS or S-2 data apply in mapping commercial forest tree species.

2.2. Data Collection

2.2.1. Satellite Data

For this study, we utilised two satellite images, Sentinel-2 (S2) imagery, which provides high-resolution data with a spatial resolution of 10 meters and a temporal resolution of 5 days and the high resolution (3 m) PlanetScope delivered as an analytical 8-band product (VNIR) received from Planet Laboratories, Inc (https://www.planet.com) (Planet Labs, 2022). The Sentinel-2 images were also acquired from the Planet Labs interface, which offers access to data processed to Level 1C, including thirteen spectral bands that cover a range of wavelengths from coastal blue to near-infrared (VNIR) (Wang et al., 2022b). To ensure the quality of the data, we selected only images with less than 20% cloud cover, prioritizing those taken on cloud-free days. The imagery data collection was aligned with the date of extraction of the reference data from the Usutu Forest stands register database, Microforest (MF), for ease of reference and verification.

2.2.2. Reference Data

For validation of the classification outcome, we used the stand register database which is managed by the Usutu Forest in a web-based application called Microforest. The Microforest database is a spatial database currently utilized by the organisation to manage all data related to forest stand boundaries and relevant attributes such as species, age, etc., road networks, forest infrastructure, etc. The system also covers the complete forestry operation lifecycle including forest operations, e.g., thinning, weeding, etc. harvest scheduling and the business suite. The database was mainly used for training and validating machine learning models, as it provides accurate, stand-level data that can be compared directly with the classifications generated from the satellite imageries.

2.2.3. Software Used

ArcGIS Pro was used to accomplish the segmentation and classification of satellite images. The ArcGIS Pro was also used for all other spatial data management, including forest stand adjustments, the development of current species maps, etc. Other GIS software like QGIS was also used for satellite image preprocessing, image enhancement and mosaicking together with the ESRI ArcGIS software, and other statistical softwares such as PAST and Microsoft Excel, which were used to extract statistical values such as stand mean age.

2.3. Methodology

Figure 2 provides an overview of the image classification approaches utilized in this research, as well as a description of necessary pre-processing steps (geometric correction, reprojection, mosaicking, and clipping).

Figure 2 provides a visual presentation of the methodological process flowchart for the study. The key steps involve; 1) satellite image download and preprocessing which entails collection of cloud free images for both S2 and PS, clipping of the data to the study area, projection and mosaicking of the data; the delineation of training samples and data processing (such as mosaicking and clipping); 2) categorization of species using RF and SVM algorithms; 3) assessment of the classification's correctness and comparison of the results from the two imageries and or with the species maps produced using the MF data.

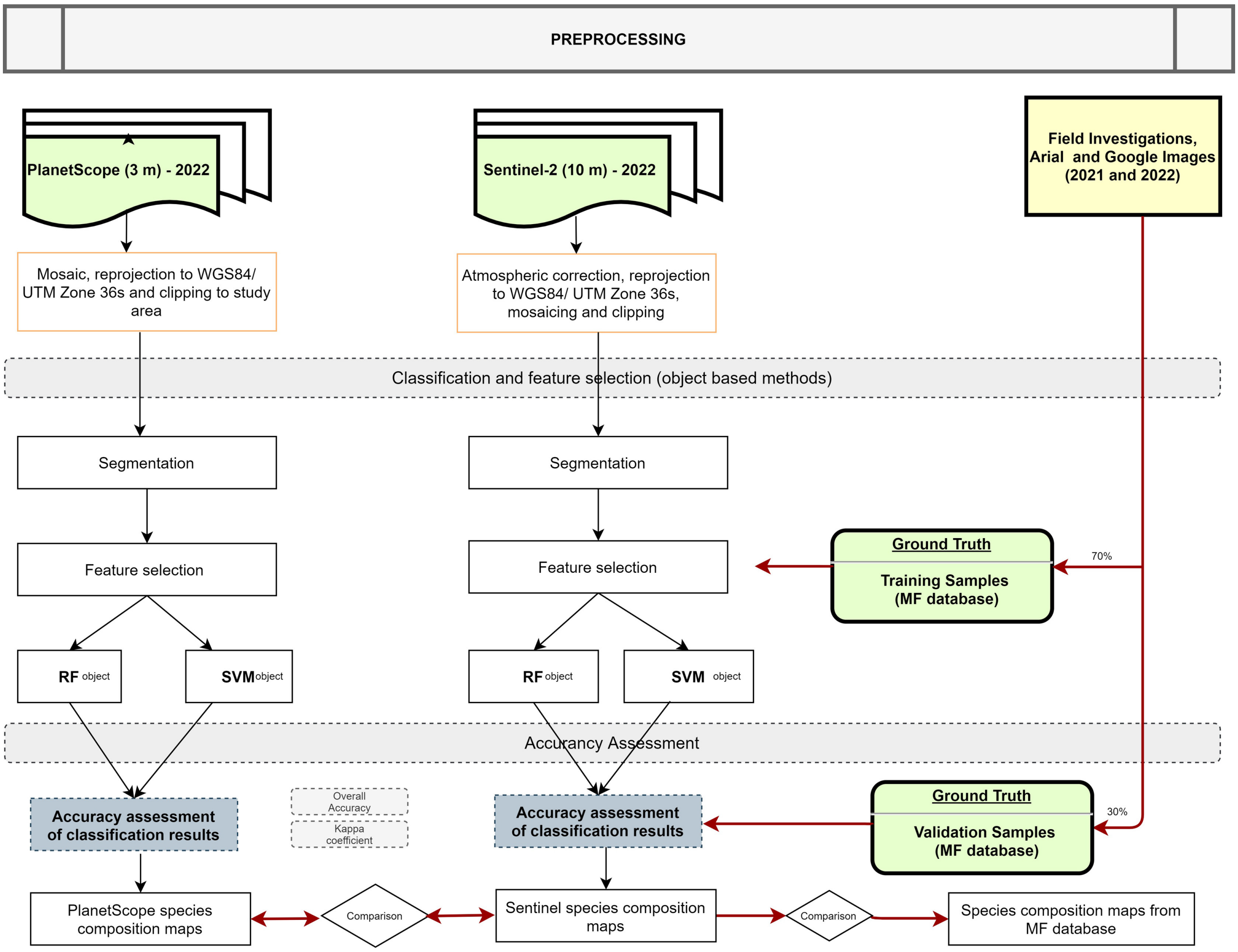


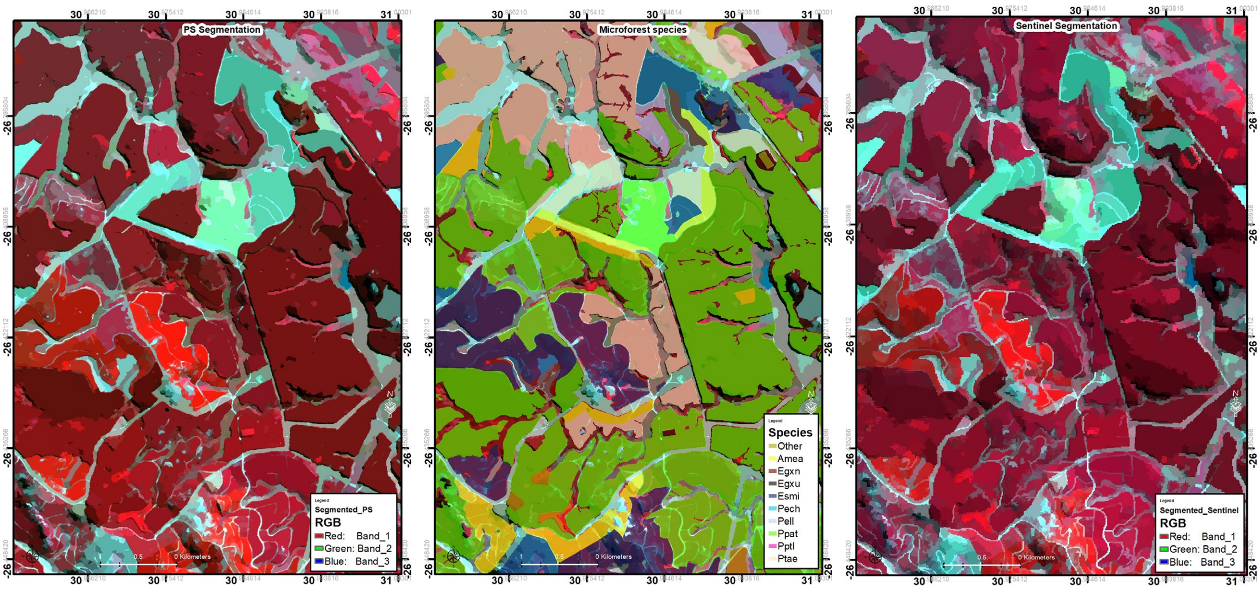
Figure 2. Flowchart of the study methods.

2.3.1. Image Preprocessing

The two satellite images, Sentinel-2 and PlanetScope were pre-processed using QGIS 3.10 and ArcGIS Pro 3.0 software. The preprocessing steps included geometric correction to ensure the spatial accuracy of the images, reprojection to the UTM zone 36S (which is the suitable coordinate system for the area) and mosaicking to create a continuous image of the study area. We also performed clipping to limit the analysis to the Usuthu Forest study area. For the Sentinel 2 image, the spectral bands were reduced from thirteen to ten by excluding those with lower spatial resolution or less relevance to the study, ensuring that the remaining bands retained the necessary pixel size and detail for accurate classification.

2.3.2. Satellite Image Segmentation

We utilised the ArcGIS Pro 3.0 software for image segmentation in this research, with an intention to streamline or alter the depiction of an image to make it significant and relatable. The first and most crucial stage in object-based image categorization is segmentation. To distinguish between surrounding heterogeneous regions, segmentation algorithms' basic goal is to combine homogeneous pixels into image elements. Satellite image segmentation was done prior to image classification and was specified as an input during species classification. For this research, the maximum segment size was set to 20, spectral and spatial detail set at 16 for the sentinel 2 imagery and set to 12 for the PS imagery. More and more research has switched from using pixel-based methodologies to object-based ones as high spatial resolution images have become increasingly prevalent. By using high spatial resolution images, prior research has demonstrated that OBIA methods offer highest level of categorization precision than pixel based methods [40]. Studies prove that the level of categorization precision is subjected to the image segmentation quality [40]. Figure 3 presents a segmentation done in the ArcGIS Pro software within the study area.



(A) (B) (C)

Figure 3. Image segmentation in ArcGisPro software. (A) PlanetScope imagery segments; (B) MF database map showing stands boundaries and species; (C) Sentinel 2 segments. The image compares the segments for the PS image on the left side of the species classification map from the reference database and the segmentation of the S2 image on the right side of the map.

2.3.3. Image Classification

In this research, we utilized two supervised classification approaches for the image categorization. The RF classification method [41]-[43] and the SVM [42]. Many different applications of remote sensing use the SVM classification technique [44] [45]. RF excels at finding important variables and has strong data processing abilities [46]. When used with very high spatial resolution satellites, RF is considered to be a reliable classification method for agricultural purposes, especially in heterogeneous environments [47] [48]. SVM and RF are frequently cited as being the two methods that perform well when handling complicated categorization issues like differentiating between tree species [49]-[51].

For each classifier, the models were trained using a stratified random sample of the commercial stands in the study area, with 70% of the data used for training and 30% reserved for validation. For this study, overall number of species stands (N) chosen for this investigation was 336, that consisted of all the different species in the study area which were proportionally sampled based on the species type as a stratum, from a total of 1712 stands in the study site. Using Geographic Information System (GIS) technologies, data was then retrieved at a stand level scale for the list of sampled stands. The models were then applied to the entire study area to generate species classification maps for both imageries in the study area. The final classification maps were then compared to the reference data from the Microforest database stands register to evaluate their accuracy.

2.3.4. Accuracy Assessment

We computed overall accuracy (OA), user accuracy (UA), producer accuracy (PA), and the Kappa coefficient using a confusion matrix to evaluate the classifications' correctness. A common technique in machine learning and remote sensing is the confusion matrix, which contrasts the actual classes from the reference data with the expected classes, such as the different species [52]. The UA and PA offer information about the classifier's performance for each class, while the OA shows the proportion of pixels that were properly identified. Taking into consideration the potential for random agreement, the Kappa coefficient calculates the degree of agreement between the reference data and the categorised map.

3. Results

3.1. Classification Accuracy of the Two Satellite Imageries

The effectiveness of each classification approach in differentiating between tree species was tested on the two separate images. The classification was performed at genus level (a family or group of tree species sharing common characteristics) and species level (a specific type of tree in the same genus) for both imageries to allow for ease of results comparison.

Both classification methods performed extremely well with the Sentinel 2 imagery when classifying the data at genus level, both achieving the highest overall accuracy of 94% and kappa of 0.90. The PlanetScope imagery produced poor classification results in both methods, with OA of 64% for the Random Forest as well as 61% by the SVM with 0.49 and 0.48 kappa for the Random Forest and Support Vector Machine, respectively, which are lower than the Sentinel 2 results. **Table 1** presents a comparison of the confusion matrix values obtained by each of the methods in the two imageries when classified at genus level.

When classifying the data at species level, the highest classification results were provided by the SVM method, with 82% OA and 0.82 kappa for the S-2 data.

Again, the results from the PlanetScope imagery indicate a further decline when classifying the data at species level. Both methods produced less than acceptable results below 55%. The classification outcomes for both imageries and methods are presented in Table 2. These findings suggest that the Sentinel 2 imagery together with the SVM method is highly effective in discriminating the different species types in the study area, both at genus and species level as it obtained highly acceptable results above 80%.

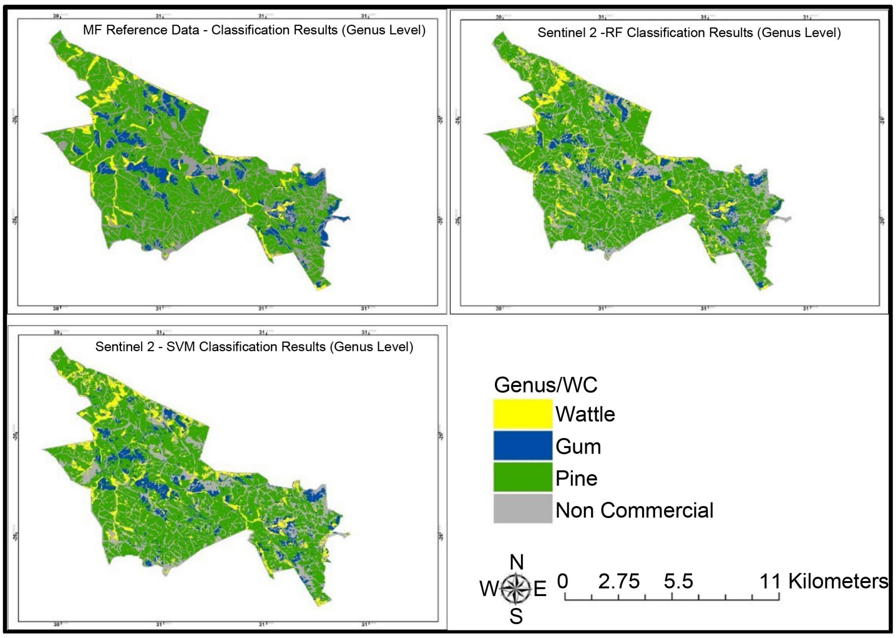
Table 1. Confusion matrix and statistical measures for Sentinel 2 and PlanetScope imageries (genus level).

Genus/WC	Sentinel 2 imagery				PlanetScope imagery			
	RF classifier		SVM classifier		RF classifier		SVM classifier	
	PA	UA	PA	UA	PA	UA	PA	UA
Wattle	88	100	100	85	63	32	94	22
Gum	96	90	93	100	89	77	81	88
Pine	99	93	97	92	54	84	46	87
Non-commercial	84	95	86	97	67	54	67	81
Overall accuracy	**94%**		**94%**		**64%**		**61%**	
Kappa value	**0.90**		**0.90**		**0.49**		**0.48**	

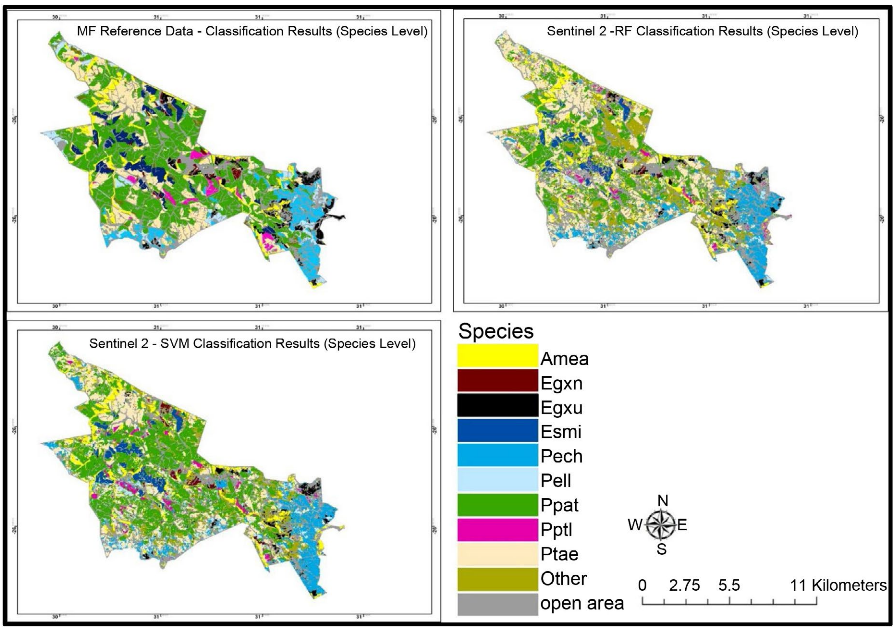
Table 2. Confusion matrix and statistical measures for Sentinel 2 and PlanetScope imageries (species level).

Species type	Sentinel 2 imagery				PlanetScope imagery			
	RF classifier		SVM classifier		RF classifier		SVM classifier	
	PA	UA	PA	UA	PA	UA	PA	UA
Amea	93	74	100	88	56	36	60	43
Egxn	67	100	83	100	83	100	83	71
Egxu	67	67	83	83	33	67	67	80
Esmi	100	86	100	100	100	86	75	100
Pech	92	34	92	41	91	45	50	20
Pell	15	100	45	100	15	63	24	47
Ppat	83	67	93	81	30	21	40	27
Pptl	50	75	83	100	17	100	33	67
Ptae	59	53	100	85	50	75	39	29
Other	44	40	67	67	44	22	22	14
Non-commercial	80	81	88	93	70	62	57	90
Overall accuracy	**65%**		**82%**		**53%**		**47%**	
Kappa value	**0.60**		**0.82**		**0.46**		**0.40**	

Figure 4(A) shows the graphical representation of S2 data, and the two classification methods results at the genus level and Figure 4(B) shows the classification outcome maps for S2 and the methods at the species level. The maps indicate a high level of agreement between the reference data and the classified maps for both methods at the genus level (Figure 4(A)) compared to the species level (Figure 4(B)) for the S2 images.



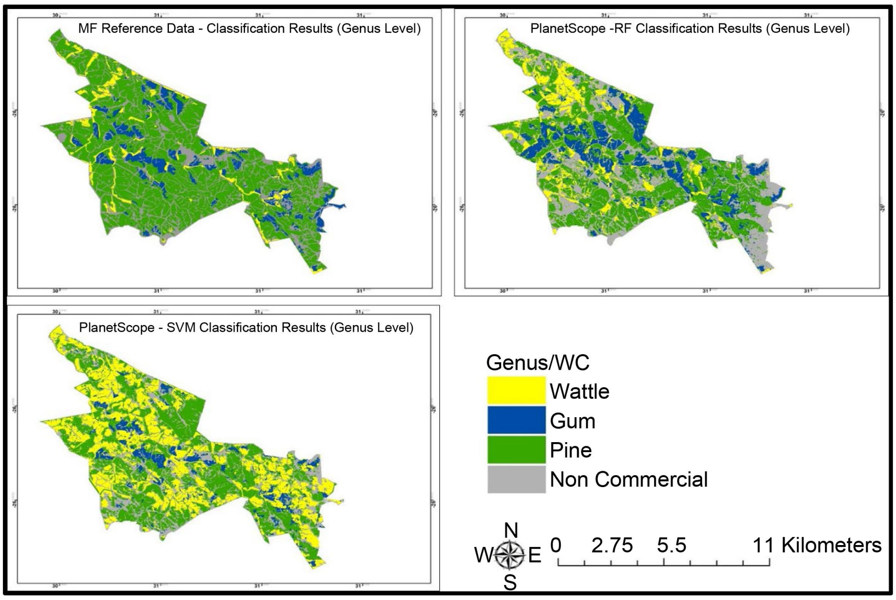
(A)



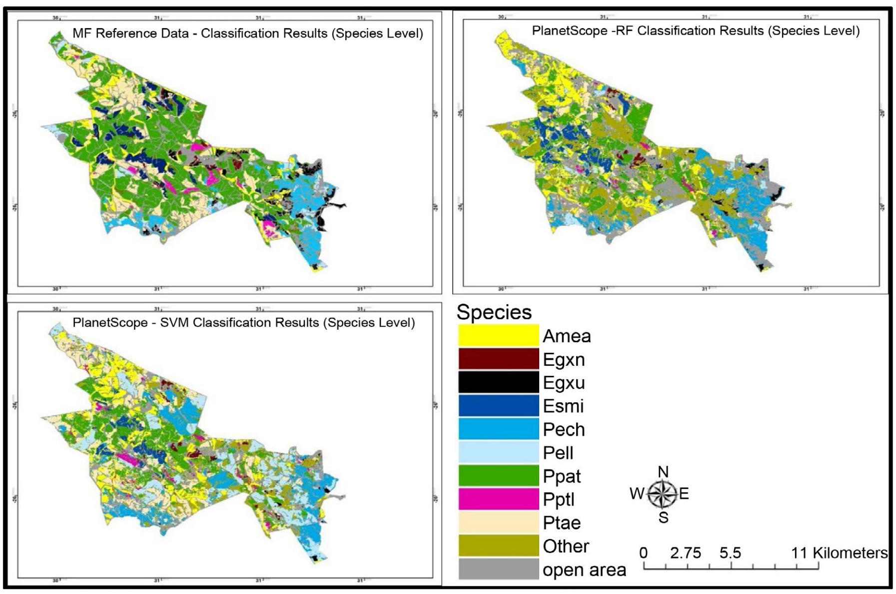
(B)

Figure 4. (A): Map comparison of Sentinel 2-RF and SVM classification results to MF data at genus level. (B): Map comparison of Sentinel 2-RF and SVM classification results to MF data at species level.

Figure 5(A) shows the graphical representation of the PS data, and the two classification methods results at the genus level and Figure 5(B) shows the classification outcome maps for PS and the methods at species level. The maps confirm the outcome of the confusion matrix, suggesting a poor level of agreement between the reference data and the classified data for the PS imagery. There are visible disparities between the reference data and the classified map both at genus and species level. A glaring difference is seen in the SVM classification outcome at the genus level whereby the map shows an overclassified wattle genus. The results show a further decline in classifying the data at species level for the PS image as shown in Figure 5(B).



(A)



(B)

Figure 5. (A): Map comparison of PlanetScope-RF and SVM classification results to MF data at genus level. (B): Map comparison of PlanetScope-RF and SVM classification results to MF data at species level.

3.2. Comparison with Reference Data

3.2.1. Compared to the Sentinel 2 Classification

The classification results for the S2 imagery were compared with the reference data from the Microforest database to evaluate their accuracy at the genus level. For each of the genus groups in each of the classification techniques, the area difference between the data that were categorized, and the reference data was determined. Both classifiers produced estimates of genus area that closely matched the reference data, with highly comparable results at less 10% of the reference data for the pine genus and the non-commercial areas as shown in Figure 6. There was a noted over estimation for the wattle genus by both classifiers of around 20% more and the gum genus was underestimated by both classifiers within 20% less.

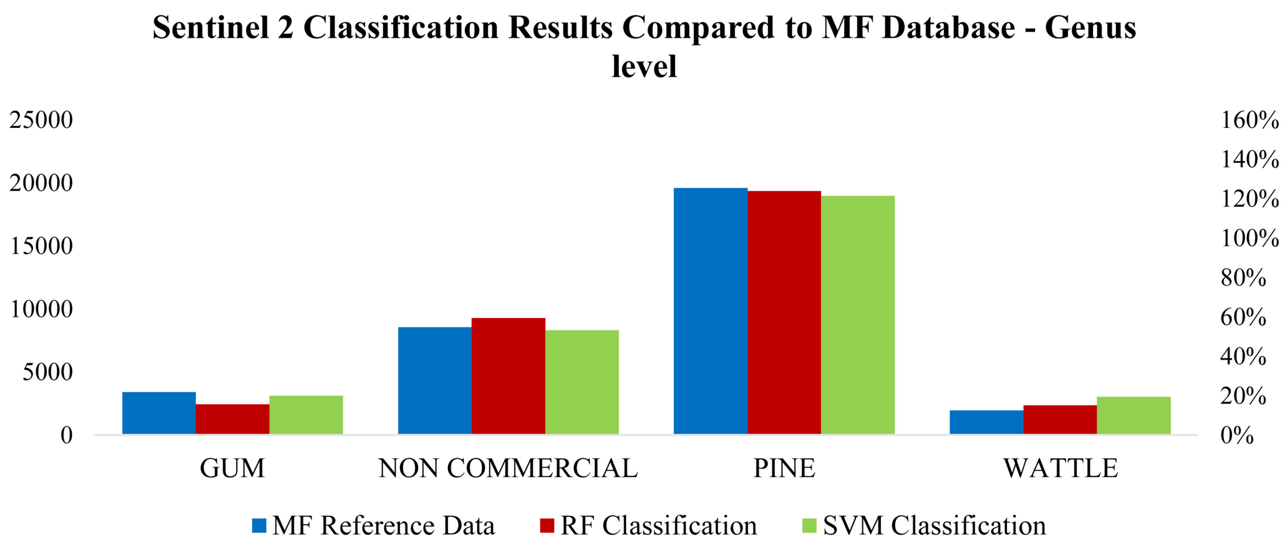
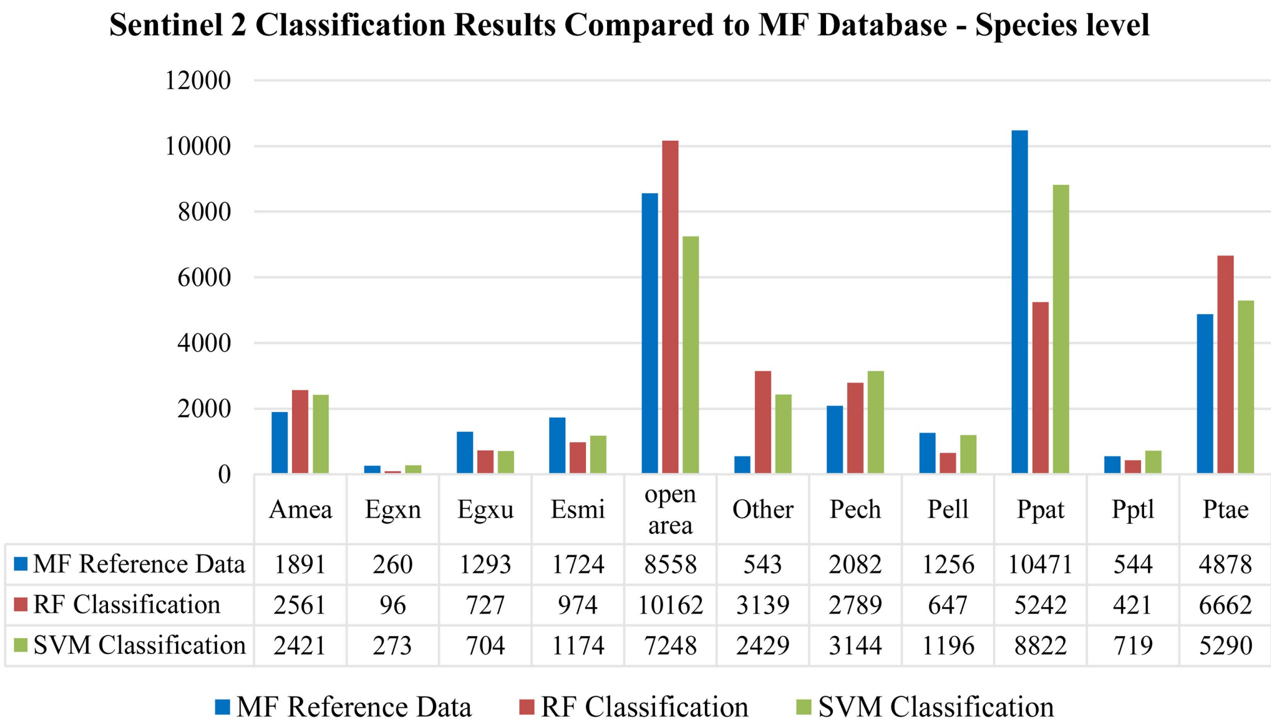


Figure 6. Sentinel 2-RF and SVM classification results compared to MF data at genus level.

Despite the satisfactory classification accuracy that was achieved by the Sentinel 2 image as per the confusion matrix at species level, several species were both overclassified and under classified by both methods, as shown in (Figure 7) for the categorized data as well as the reference data. Most differences appeared to be statistically significant, according to the graph. Species under the gum genus (e*gxn*, *egxu and Esmi*) were mostly under classified by both models while most of the pine and wattle genus species (*Pech*, *Ptae*, and *Amea*) were over estimated. However, as indicated in the results in Figure 7, the SVM consistently produced a closer value to the reference data when compared to the RF method which suggests that the SVM, when applied to Sentinel-2 imagery, can produce reliable and accurate maps of the Usutu Forest plantation at both the genus and species level.

3.2.2. Compared to the PlanetScope Classification

For each of the genus groups in each of the classification techniques, the area difference between the data that were categorized, and the reference data was also determined for the PlanetScope imagery. As shown in Figure 8, both classifiers



	Amea	Egxn	Egxu	Esmi	open area	Other	Pech	Pell	Ppat	Pptl	Ptae
MF Reference Data	1891	260	1293	1724	8558	543	2082	1256	10471	544	4878
RF Classification	2561	96	727	974	10162	3139	2789	647	5242	421	6662
SVM Classification	2421	273	704	1174	7248	2429	3144	1196	8822	719	5290

Figure 7. Sentinel 2-RF and SVM classification results compared to MF data at species level.

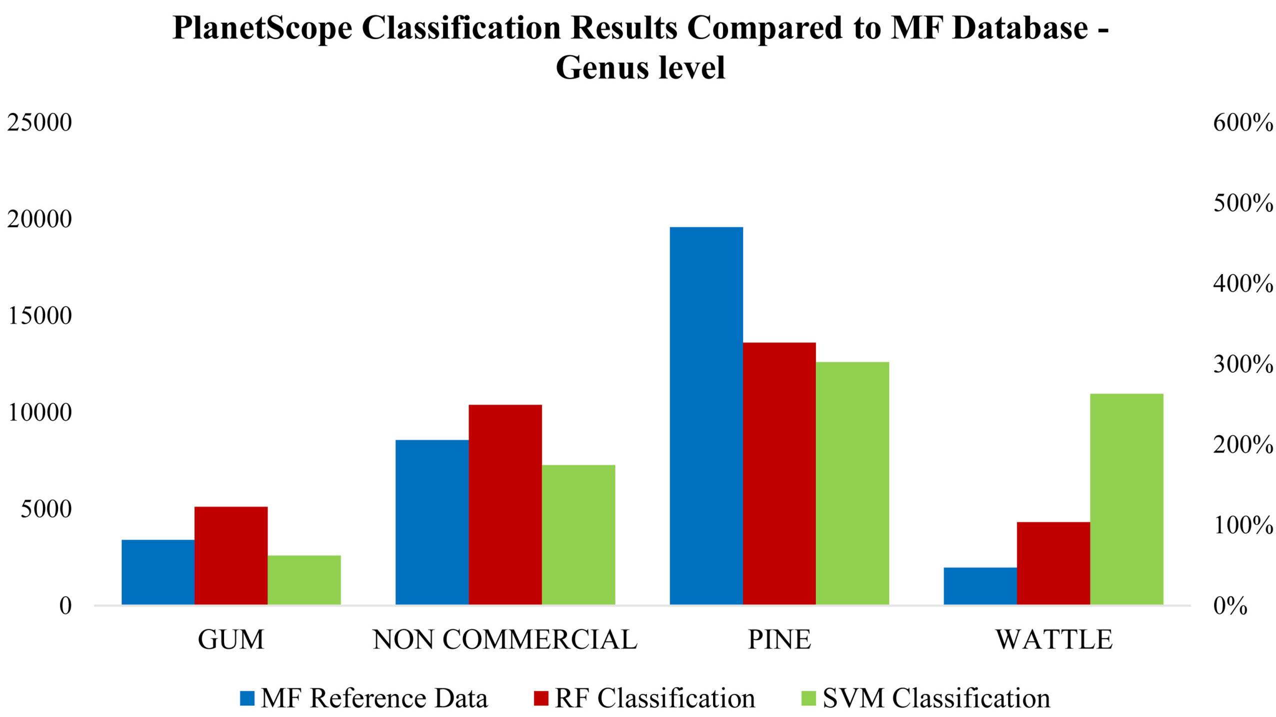
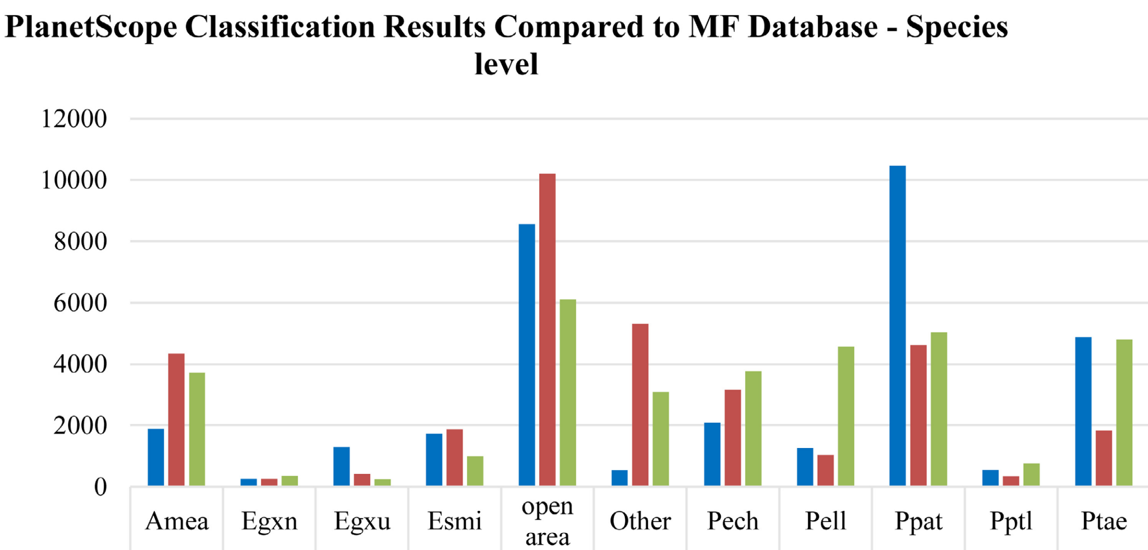


Figure 8. PlanetScope-RF and SVM classification results compared to MF data at genus level.

produced incomparable estimates of the classified data to the reference data at genus level. The classification results indicate an overestimation of the area for wattle of over 100% for both methods and for pine, the results indicate a significantly very bad underestimation of the area by both methods. The gum and non-commercial areas indicate less discrepancies among the categorized data as well as the data used for reference within the research site.

When classifying the data at the species level, the PlanetScope imagery shows a further drop in accuracy level with both techniques. As seen in (**Figure 9**) for both the reference data and the categorised data, most species were both overclassified and underclassified by both methods. As confirmed by the confusion matrix, both classifiers performed poorly with less than 55% and the classified areas are highly incomparable to the reference data across all species types. Using the high resolution PlanetScope imagery, both approaches consistently overestimate and underestimate species types. Given the large degree of disagreement at both the genus and species levels, it is not advisable to utilise these machine learning techniques on the PlanetScope imagery within the Usutu Forest plantation because they result in inaccurate maps of the species types. The findings imply that, in comparison to high spectral S2 data, high-resolution PlanetScope imaging is less able to distinguish between different species kinds in the research area.



	Amea	Egxn	Egxu	Esmi	open area	Other	Pech	Pell	Ppat	Pptl	Ptae
MF Reference Data	1891	260	1293	1724	8558	543	2082	1256	10471	544	4878
RF Classification	4344	264	426	1877	10202	5306	3162	1042	4628	339	1830
SVM Classification	3717	357	252	986	6104	3089	3762	4561	5030	761	4800

Figure 9. PlanetScope-RF and SVM classification results compared to MF data at species level.

4. Discussion

This study compares the capabilities of Sentinel-2 and PlanetScope imageries and machine learning techniques in mapping and discriminating commercial tree species in Eswatini. The findings show that Sentinel 2 with SVM classification method is highly suitable for identifying the different tree species, both at genus and species level within the Usutu Plantation. The PlanetScope imagery is not recommended for discriminating the different tree species in the study area as it poorly performed in classifying the data at both genus and species levels, making it a less preferred image for the task over the S2 images. The SVM classification method demonstrated superiority over the RF method in classifying the different species in the study area. There was a noticeable decline in the classification accuracy with the level of data classification and the type of imagery. A decline in classification accuracy from genus level to species level and a further decline in accuracy from the S2 image to PlanetScope was observed.

The findings are consistent with results from other researchers, e.g. [53]-[55], whose work discovered how effectively Support Vector Machine methods work with object-based image analysis. In other studies, from different disciplines, the SVM classifiers were also proven to be the most effective for spectral categorization [56] [57]. Numerous studies also highlight the superior performance of S2 images over PS images in classifying different plant species [58] [59]. For example, the study done by [60], in classifying Pedicularis invasive plant species in China, had an accuracy of 0.97 for the S2 and a slightly lower accuracy of 0.82 for the PS images, suggesting that S2 images with high spectral resolution are preferred for species identification over PS images of high spatial resolution as shown by our results. Perhaps numerous reasons for performance inconsistencies amongst machine learning algorithms exist, according to [61], one being the reliance on the training data, which includes factors like quality, the number of test sets for each variable or object, and infield verification features. Since, machine learning algorithms heavily rely on the caliber of training data as well as the chosen areas [61], the samples used to train the prediction models, are probably what accounts for the SVM classifier's somewhat improved performance in this research. Future research on species discrimination in the area should examine more hyperspectral images, optimise spectral band selection, and investigate alternative machine learning techniques that might provide extra advantages, as indicated by the poor performance of the high resolution multispectral, PlanetScope imagery in terms of classification accuracy.

This study does, however, have certain drawbacks. The results may not be as broadly applicable as they may be, because the study concentrated on a specific geographic area with almost a similar climate and terrain. Future studies on species discrimination should consider extending the study to other regions with different environmental conditions and landscapes to further validate the findings and improve the robustness of the classification models. Future research should investigate the incorporation of other data sources such as merging hyperspectral images with LiDAR data, to extract more detailed structural features such as internal foliage and branch patterns of an individual tree and consider utilising various vegetation indices to improve the classification accuracy.

5. Conclusions

In conclusion, this study's results have shown that Sentinel-2 imagery, combined with machine learning techniques, can be effectively used to discriminate different forest tree species in the Usutu Forest, Eswatini. The SVM classifier achieved a classification accuracy that is highly acceptable both at the species and genus level when classifying the Sentinel 2 data, outperforming RF in terms of accuracy and reliability. The PlanetScope imagery produced very unreliable classification results with both machine learning methods, at genus and species level. These findings showcase the potential of remote sensing and machine learning as tools for sustainable agriculture and offer valuable data for improving forest management practices in the Kingdom of Eswatini.

Future studies should seek to improve the existing processes by adding more data sources, investigating novel machine learning approaches, and expanding the investigation to other areas. This will enable us to develop more accurate and scalable forest plantation monitoring systems that will support the global adoption of sustainable silviculture practices.

Highlights

- Sentinel-2 imagery is highly effective in discriminating tree species in Eswatini forests than PlanetScope.
- Support Vector Machine (SVM) outperforms Random Forest (RF) in forest species classification.
- A higher classification accuracy is achieved when classifying at genus level than species level.
- Study advances cost-effective remote sensing for silviculture practices.

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Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Conflicts of Interest

The author declares no conflicts of interest.

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