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Modeling the Spatial Distribution of Acacia *decurrens* Plantation Forests Using PlanetScope Images and Environmental Variables in the Northwestern Highlands of Ethiopia

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Abstract: Small-scale Acacia *decurrens* plantation forests, established by farmers on degraded lands, have become increasingly prevalent in the Northwestern Highlands of Ethiopia. This trend has been particularly notable in Fagita Lekoma District over the past few decades. Such plantations play a significant role in addressing concerns related to sustainable agricultural land use, mitigating the adverse effects of deforestation, and meeting the livelihood and energy requirements of a growing population. However, the spatial distribution of Acacia *decurrens* and the essential remote sensing and environmental variables that determine its distribution are not well understood. This study aimed to model the spatial distribution of Acacia *decurrens* plantation forests using PlanetScope data and environmental variables combined with a species distribution model (SDM). Employing 557 presence/absence points, noncollinear variables were identified and utilized as input for six SDM algorithms, with a 70:30 split between training and test data, and 10-fold bootstrap replication. The model performance was evaluated using the receiver operation characteristic curve (AUC) and true skill statics (TSS). The ensemble model, which combined results from six individual algorithms, was implemented to predict the spatial distribution of Acacia *decurrens*. The highest accuracy with the values of 0.93 (AUC) and 0.82 (TSS) was observed using random forest (RF), followed by SVM with values of 0.89 (AUC) and 0.71 (TSS), and BRT with values of 0.89 (AUC) and 0.7 (TSS). According to the ensemble model result, Acacia decurrens plantation forests cover 22.44% of the district, with the spatial distribution decreasing towards lower elevation areas in the northeastern and western parts of the district. The major determinant variables for identifying the species were vegetation indices, specifically CVI, ARVI, and GI, with AUC metric values of 39.3%, 16%, and 7.1%, respectively. The findings of this study indicate that the combination of high-resolution remote sensing-derived vegetation indices and environmental variables using SDM could play a vital role in identifying Acacia *decurrens* plantations, offering valuable insights for land use planning and management strategies. Moreover, comprehending the spatial distribution's extent is crucial baseline information for assessing its environmental implications at a local scale.

Keywords: Acacia *decurrens*; Fagita Lekoma; PlanetScope image; plantation forests; SDM

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1. Introduction

Plantation forests are forests established by planting or deliberate seeding to achieve principally economic goals [1] such as timber, energy, fiber, and non-woody forest products [2]. They are also established for soil and water conservation and carbon sequestration in the process of afforestation and reforestation [3]. According to the FAO [2] report, plantation forests cover about 131 million ha worldwide and account for 3% of the global forest.

Between 1990 and 2020, their area increased by 55.8 million ha, with the biggest jump (21.2 million ha) recorded between 2000 and 2010.

The impact of plantation forests on the environment will depend on what land use they replace [4]. If they are established on frequently cultivated land for a long time or degraded lands, they may provide substantial opportunities for biodiversity conservation [5] and deliver vigorous ecosystem service [6], but plantations converted from the natural forest have adverse impacts on biodiversity [7]. Plantation forests are essentially significant in fragmented landscapes, where they may account for a large amount of remaining forest habitat [8] and can serve as corridors between habitats [4].

Small-scale plantation forests initiated by farmers on degraded lands have become important in Ethiopia, particularly since the mid-1990s [9]. An estimated area of 754,900 ha of the country is covered by small-scale plantation forests, and of this, 84.7% (639,400 ha) is found in the Amhara Region [9]. Critical levels of land degradation and reduced productivity forced farmers to start planting trees, often with predominantly exotic and fast-growing species at the expense of crop production [10–12].

In the Northwestern Highlands of Ethiopia, specifically in the Fagita Lekoma District, the study site and one of the districts in the Amhara Region, growing Acacia *decurrens* plantations on small-size farmlands have been rapidly increasing and are widely planted because of the economic and environmental benefits. This species is preferable due to its advantages of a fast-growing rate and adaptability to degraded and acidic soil conditions [13]. Additional reasons that motivate farmers to plant this species are its use as fuel and construction wood, animal fodder, charcoal production and availability of market, and soil fertility maintenance [14]. It also creates job opportunities for landless community parts and supports local livelihoods and rural developments, especially when managed by smallholders [13,15]. Land-use change from cultivated land and grassland into Acacia *decurrens* plantation has been common in the district in the past three decades and resulted in an increase in the forest cover of the district by more than 250% between 1887 and 2015 [16], and around 400% between 2006 and 2017 [17]. A range of ecosystem services can be obtained from plantation forests established on degraded lands that require restoration [18]. New plantation forests generated from former agricultural land can improve ecosystem service [19].

The rapid expansion of plantation forests significantly affects climate, hydrology, biodiversity, and the terrestrial carbon cycle. The expansion of plantation forests can amend the understory climate condition and soil properties [20], and water quality [21]. These changes occur as a result of changes in temperature, rainfall, land use type, and storm frequency and magnitude [4]. In addition, plantation forests can contribute strongly to regulating the environment, biodiversity, and socioeconomic functions, especially carbon sequestration [22]. To monitor such dynamics, remote sensing is an essential and effective source of data [23].

Remote sensing technologies drive developments in forest resource assessments and monitoring at various scales. They enable the provision of airborne and spaceborne data with a higher spatial resolution, frequent coverage, and expanded spectral coverage [24]. The remote sensing-based assessment of forest study is repetitive, affordable, competent, and non-destructive for monitoring [25]. Recently, in complementarity with field data, it has shown great adaptability in environmental studies such as droughts [26], floods [27], the spread of invasive species [28], disturbance [29], and other human-induced pressures [30]. The contribution of satellite data is becoming impressive to monitor the spatial distribution and temporal dynamics of plantation forests [31]. Optical data are spectrally sensitive to different species and can distinguish phenological characteristics unique to a particular plantation [32]. Different plantation forests can have distinct implications for the local ecosystem service [33].

The geographic distribution of species is dynamic at accelerating rates because of anthropogenic pressures, the introduction of non-native species, and climate change [34]. To understand the distribution of introduced or expanding species, researchers often map the suitability status of the habitat or the potential occurrence probability of species using different techniques such as expert opinion [35], mathematical models [36], or machine learning algorithms [37]. These methods help researchers and decision-makers to identify priority areas for environmental conservation [38], examine landscape planning approaches on the management and restoration of protected areas [39], assess species distribution under changing anthropogenic or environmental conditions [40], investigate the impact of environmental changes on the biodiversity [41], and model the invasion status of invasive species [28,42].

The species distribution model (SDM) is a popular technique in ecology and conservation biology to assess the impact of land use and climate changes on biodiversity distribution [43], predict species diversity and composition patterns over space and time [44], and provide spatially explicit and compressive maps that are specifically important to understand the distribution level and extent of a given species. It combines observations of species occurrence or abundance with environmental variables [45]; its performance depends on the collected data during field surveys and exists as simple presence/absence records, which are crucial to train and validate the model [46]. Moreover, the accuracy of SDM varies among algorithms [47], and integrating multiple algorithms is more reliable to get robust estimations of species distribution [48].

The use of SDM algorithms in combination with remotely sensed datasets is effective for mapping plant species across different management levels at local and regional scales [49]. In Sub-Saharan Africa, agricultural landscapes are highly fragmented and this is one of the challenges complicating their mapping [50]. Fragmented parcels of land with verities of coverage highlighting the need of methods based on high resolution satellite imageries [51].

PlanetScope (PS) satellite constellation can achieve daily coverage with a spatial resolution of 3–5 m, visible to near-infrared and atmospherically corrected imagery [52], which has been successfully applied in many fields, for example, rubber plantation mapping [53], forest canopy height estimation [54], biomass estimation [55], leaf area index production [56], cropland mapping [51], and crop yield prediction [57]. It provides effective spatial data for the extraction of plantation forest and agricultural information in the tropical and subtropical regions [58], and offers a good opportunity to overcome challenges in mapping smallholder agricultural fields [51].

Understanding the interplay between the spatial distribution of a species and its environmental determinants is a fundamental concept in ecology and conservation [59]. Establishing plantation forests on agricultural or degraded land presents significant prospects for biodiversity conservation [60]. Consequently, the impact of plantation forests is contingent upon their spatial extent of landscape coverage [61] and the specific land use they replace [4]. Despite prior studies in the study area focusing primarily on land use/land cover changes across all classes [11,16,17,62,63], there is a noticeable gap in research specifically addressing the species-level identification of Acacia *decurrens* plantations through the utilization of high-resolution satellite imagery and environmental variables combined with machine learning algorithms. Examining such a spatial pattern is crucial in any study aiming to ensure the provision of goods and services [61]. Therefore, the objectives of this research were (i) to model the spatial distribution of Acacia *decurrens* plantation forests using high-resolution satellite imagery, (ii) to evaluate the performance of SDM algorithms for Acacia *decurrens* distribution modeling, and (iii) to identify the relative importance of predictor variables for Acacia *decurrens* distribution modeling. Modeling and understanding the spatial spread of such species are high priorities for resource managers to assess the environmental implications of the sustained use of plantation forests and to scale up for the other degraded areas of the country based on scientific findings and with great attention. This is because in Ethiopia, it is believed that small-scale tree plantations can contribute to addressing issues related to sustainable agricultural land use, mitigating the negative impacts of deforestation, and meeting the needs for the livelihood and energy of the growing population [64]. Having comprehensive information about its distribution enables effective control and management.

2. Data and Methods

2.1. Study Area

The study was conducted in Fagita Lekoma District which is part of the Northwestern Highlands of Ethiopia. The total area of the district is 65,579 ha [16], where the elevation extends from 1879 m to 2922 m above sea level (Figure 1). The mean daily temperature in the district ranges from 15 °C to 24 °C, and it receives an average annual rainfall of 2454 mm, with peak precipitation occurring between June and September [65]. The climatic conditions in the study area comprise 84% humid subtropical (*Weynadega*) and 16% moist subtropical (*Dega*) agroecological zones [16].

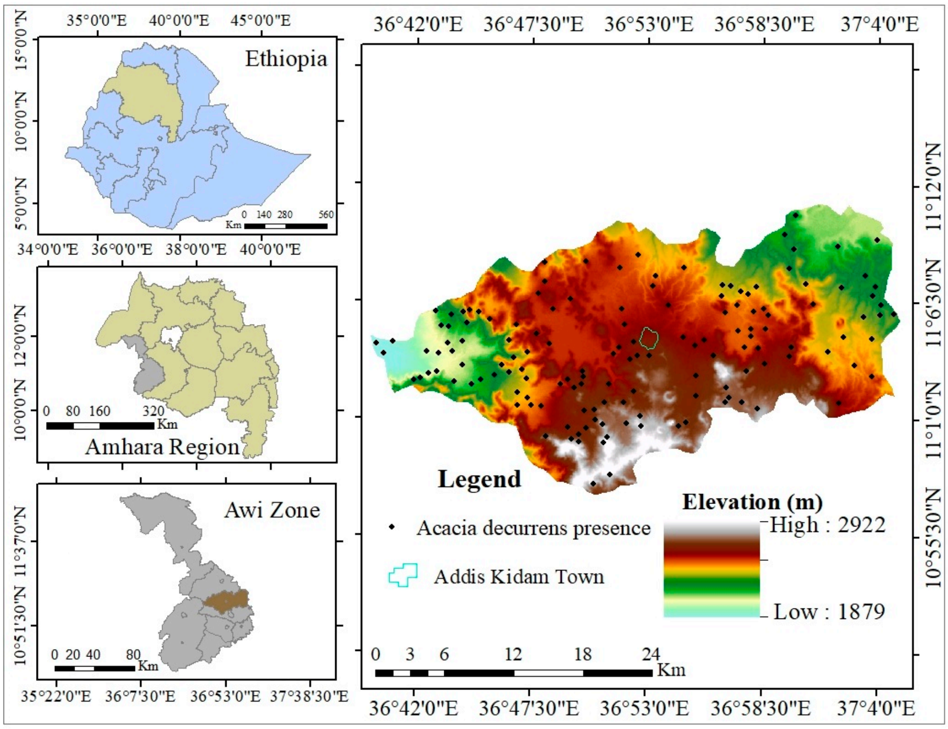

Figure 1. Map of Fagita Lekoma District.

The major economic activity in the area is a mixed crop–livestock system [66] and recently, charcoal production from Acacia decurrens plantation has become another significant source of income for residents [67], replacing crop and grazing lands [16]. Consequently, the vegetation status of the district has increased over the last two decades, resulting in an improvement in the ecosystem condition [68].

2.2. Data

2.2.1. Remote Sensing Data

The PS satellite constellation comprises more than 180 satellites in orbit, allowing it to provide high-resolution data with daily global coverage [69]. For this study, cloud-free data from the PS satellite for February 2022 were collected. The images were a level 3B product that had undergone pre-processing, including radiometric and geometric correction [58]. They had a spatial resolution of 3m and consisted of four bands in the visible (blue, green, and red) and near-infrared regions of the spectrum. An image mosaic was created for six scenes of the PS image using QGIS 3.28 to fully cover the study area. Then, it was projected to Adindan Universal Transvers Mercator (UTM) Zone 37N.

Vegetation indices (Appendix A), known for their capabilities in detecting and mapping the distribution of plant species, were selected from the Index Database (https://www.indexdatabase.de/ accessed on 17 March 2023). Indices that have proven effective in characterizing various vegetation types were selected, particularly those sensitive to reflectance in the visible and NIR regions. These regions have been recognized as effective in discriminating commercial forest species [70]. The four spectral bands of PS and the thirty-one vegetation indices derived were tested to identify Acacia *decurrens* plantation forest species.

2.2.2. Environmental Variable Data

In addition to the remote sensing data, environmental variables such as elevation, slope, aspect, road proximity, temperature, and rainfall were used in this study. These variables can be categorized as climatic and topographic variables.

A significant correlation exists between climatic factors, such as temperature and rainfall, and the spatial distribution of forest cover [71]. Rainfall data from Climate Hazard Group InfraRed Precipitation with Station data (CHIRPS) were acquired from the Famine Early Warning Systems Network (FEWS NET) dataset, accessible at a spatial resolution of 5 km (https://earlywarning.usgs.gov/fews accessed on 24 March 2023). Additionally, land surface temperature (LST) data from Moderate Resolution Imaging Spectroradiometer (MODIS), with a spatial resolution of 250 m, were utilized for temperature data. It is noteworthy that forests can influence local temperatures, including LST [72].

Vegetation dynamics were determined using topographic factors such as elevation, slope, and aspect [73,74], as well as road accessibility [75]. Aspects, elevations, and slopes intricately govern the spatial and temporal distribution of critical elements, including radiation, temperature, and precipitation, thereby significantly influencing species composition [76]. A digital elevation model (DEM), extracted from ALOS PALSAR with a spatial resolution of 12.5 m (https://search.asf.alaska.edu/#/ accessed on 24 March 2023), was used to generate topographic variables such as the elevation, aspect, slope, and streams of the study area. The heterogeneity of soil types gives rise to niches characterized by specific conditions, consequently influencing the distribution patterns of plants [77]. All variables underwent various pre-processing stages, which involved resampling to match the spatial resolution of PS imagery and masking to align with the study area's extent using QGIS 3.28.

2.2.3. Presence/Absence Data

Presence/absence data were collected in the field using Garmin eTrex GPS with an error below two meters, concurrently with the capture of PS imagery in February 2022. A stratified random sampling, based on land use/land cover types, was employed. A total of 557 points were collected, with the distribution proportional to the extent of each land use/land cover type in the district. Of these, 195 points (35%) represented presence data in Acacia *decurrens* planted areas, while the remaining 362 points (65%) were collected in croplands, grasslands, natural forests, and settlement areas. The proportions were determined based on previous studies conducted in the district by Teshome and Wondimu [62] and Worku et al. [63]. The minimum distance between two consecutive points was two hundred meters, and the Spatially Rarefy Tool in the SDM ToolBox v2.10 under ArcGIS 10.8 was used to reduce the spatial autocorrelation between points.

2.3. Variable Selection

Multicollinearity among predictor variables (i.e., remote sensing and environmental variables) was assessed using the Variance Inflation Factor (VIF) step (*vifstep*) function of usdm package. Variables above the threshold (greater than 10) were considered as collinear and excluded from further processing [78]. This test aids in the selection of predictor variables by assessing their relative importance [79].

2.4. Modelling Algorithms

Numerous SDM algorithms have been developed to predict species distribution based on environmental factors [80]. In this study, SDM was employed using six commonly used algorithms, which can be categorized into two regression methods, namely, generalized linear models (GLMs) [81] and multivariate adaptive regression spline (MARS) [82]; three machine learning methods, namely, boosted regression trees (BRT) [83], random forest (RF) [84], and support vector machine (SVM) [85]; and one classification and regression method, namely, classification and regression trees (CART) [86]. Furthermore, the prediction results of individual algorithms were combined based on their weighted mean of TSS to create an ensemble model [87], which is widely recognized as a powerful, well-referenced, and stable method for tree species prediction [88]. The weights assigned to the ensemble model were determined proportionally to the computed TSS derived from the cross-validation runs of the best performing models. This methodology ensures a nuanced and optimized weighting scheme for the ensemble model within the context of each model's performance across multiple cross-validation iterations [89], and significantly enhances the accuracy of SDM [47].

2.5. Model Evaluation

Models were calibrated with 70% of the presence/absence data, while the remaining 30% were utilized to evaluate the predictive performance of each model [90]. This evaluation involved a 10-fold bootstrap replication, employing both threshold-independent metrics, such as area under a receiver operating characteristic (ROC) curve (AUC) [91], and threshold-dependent metrics, such as the true skill statistic (TSS) [92].

The AUC metric evaluates a model's ability to distinguish between sites where a species is present and those where it is absent. It serves as an indicator of how effectively the models prioritize areas based on their suitability as habitat for a particular species [93]. A model is deemed excellent when the AUC is greater than 0.9, good for values between 0.8 and 0.9, acceptable for values between 0.7 and 0.8, poor for values between 0.6 and 0.7, and invalid for values between 0.5 and 0.6 [90].

The TSS is calculated as sensitivity (the proportion of observed presence to predicted presence, or true positive rate) plus specificity (the proportion of observed absence to predicted absence, or true negative rate) minus one [91]. TSS is not sensitive to prevalence, while keeping all the advantages of Kappa, such as considering omission and commission errors [92]. The TSS value ranges from −1 to 1, where +1 indicates perfect agreement between observations and predictions, and values of 0 or less implies results not better than random grouping [94]. The overall workflow adopted in this study is outlined in Figure 2 below.

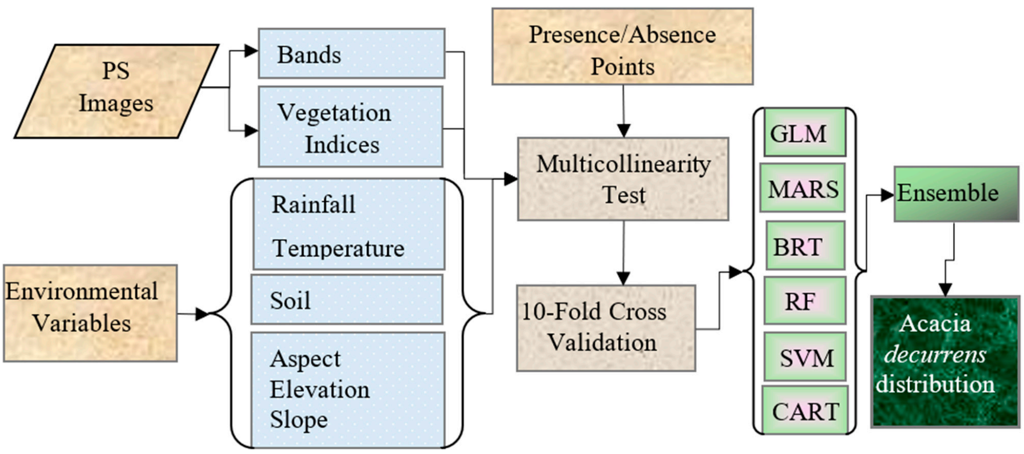

Figure 2. An overview of the methodological framework applied in the predictive modeling of Acacia *decurrens* distribution.

3. Results

3.1. Multicollinearity Test

Strongly correlated variables were eliminated using the multicollinearity test. Out of forty-two variables used on the test, eleven predictor variables with a VIF below the specified threshold were selected (Table 1). Atmospheric Resistant Vegetation Index (ARVI), Aspect, Chlorophyll Vegetation Index (CVI), Green Index (GI), Modified Soil Adjusted Vegetation Index (mSAVI), Elevation, Rainfall, Road, Soil type, Slope, and Temperature were the variables that satisfied the VIF threshold value. After excluding the collinear variables, the linear correlation coefficients ranged between 0.004907765 (Soil type~GI) and 0.8013945 (CVI~ARVI).

Table 1. VIFs of the predictive variables after multicollinearity test with a cut-off threshold of 10.

No.	Variables	VIF
1	ARVI	7.414995
2	Aspect	1.190828
3	CVI	6.169403
4	Elevation	3.323751
5	GI	3.797256
6	mSAVI	3.771155
7	Rainfall	3.080133
8	Road	1.192230
9	Slope	1.220056
10	Soil type	1.724052
11	Temperature	5.638469

3.2. Performance of Modelling Algorithms

All modelling algorithms for Acacia *decurrens* identification were generally effective in terms of both AUC and TSS values (Figure 3 and Table 2). AUC values ranged between 0.84 (GLM and CART) and 0.93 (RF). TSS ranged from 0.64 to 0.81 (Table 2). RF received the highest TSS, and GLM received the lowest TSS among all SDM algorithms. GLM, CART, and MARS had the lowest performance out of all six algorithms based on both AUC and TSS values, and RF achieved the highest performance. ROC plots are graphical representations of sensitivity (the true positive rate) plotted against 1-specificity (the false positive rate). In these plots, an algorithm that exhibits a curve closer to the top-left corner demonstrates superior performance compared to an algorithm with the curve closer to the 45-degree line within the ROC space. For instance, the ROC plots generated using the GLM and CART algorithms (Figure 3) exhibit a section of the plot that leans closer to the 45-degree line, indicating relatively lower performance. These results are different from the RF ROC plots, which illustrate relatively higher performance. Sensitivity and specificity scores were high across all algorithms, signifying the effective identification of both the presence and absence areas of Acacia *decurrens* (Table 2). This indicates that the proportion of correctly classified samples was maximum.

The presence values of Acacia *decurrens* plantation forest for the GLM, MARS, BRT, RF, SVM, and CART algorithms were 19.07%, 23.56%, 19.09%, 23.48%, 24.15%, and 24.72%, respectively. The best performing RF algorithm shows that Acacia *decurrens* covered an area of approximately 15,818.53 ha within the study area.

Ensemble modeling was employed to combine all the selected algorithms, reducing bias, and providing a relative evaluation of the significance of each predictor variable across all chosen modeling algorithms, with the intention of enhancing prediction performance [45]. According to the ensemble model result, 14,203.97 ha (22.44%) of the district was covered by Acacia *decurrens*, with a higher prevalence in the Southcentral and Central regions (Figure 4).

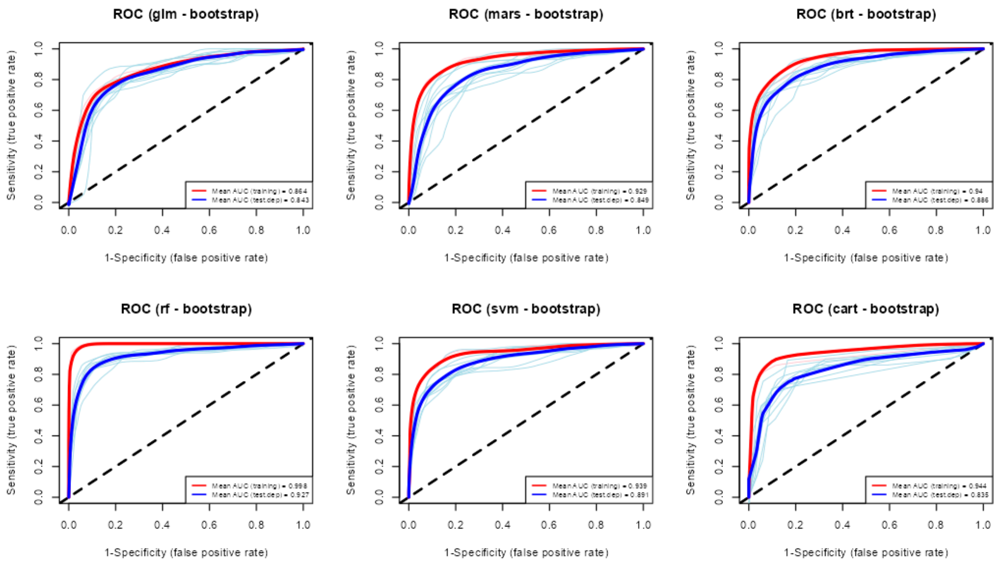

Figure 3. ROC curves generated using ten-fold bootstrap replication for the applied algorithms to identify the distribution of Acacia decurrens. The vertical axis represents sensitivity (true positive rate) and the horizontal axis represents 1-specificity (false positive rate), depicting the proportions of correctly and incorrectly classified samples. The red and blue smoothed curves stand for the mean AUC when using training and testing data, respectively.

Table 2. Performance of SDM algorithms for Acacia *decurrens* prediction.

Algorithm	AUC	Sensitivity	Specificity	TSS
GLM	0.84	0.81	0.83	0.64
MARS	0.85	0.82	0.83	0.65
BRT	0.89	0.83	0.87	0.7
RF	0.93	0.9	0.92	0.82
SVM	0.89	0.82	0.89	0.71
CART	0.84	0.8	0.85	0.65

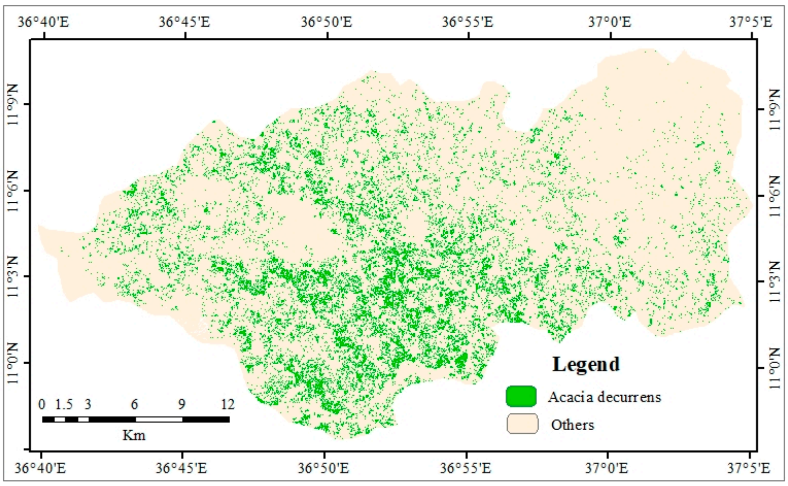

Figure 4. The spatial distribution of Acacia *decurrens* from the ensemble model.

3.3. Variable Importance

CVI is the most contributing variable, followed by ARVI and GI, based on the average result of all used SDM algorithms. Most of the environmental predictors have relatively the same contribution for Acacia *decurrens* prediction (Figure 5). Moreover, the relative importance of each variable for Acacia *decurrens* identification determined and variables with below 1% contribution (Aspect and Soil type) were excluded from the final modelling [95].

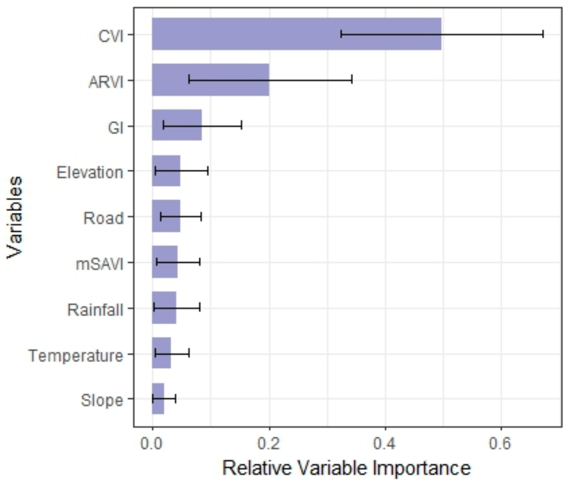

Figure 5. Relative importance of variables for Acacia *decurrens* prediction.

The optimal environmental conditions that best represent the occurrence probability of Acacia *decurrens* concerning both the vegetation indices and environmental variables are presented in Figures 6 and 7, respectively. They provide a quantitative representation of the relationship between predictors and the logistic probability of an Acacia *decurrens* distribution. These curves assist in comprehending the ecological niche of the Acacia *decurrens* within the predictor's range. Peaks in each curve indicate the values that influenced optimal model performance. The shape, the location of the peak, and the range of values around the peak provide valuable information that influences the distribution of Acacia *decurrens*. Among vegetation indices, the response curves with the highest peak value were observed for CVI, with a high probability in areas that have a value between ~30 and 40, followed by GI (~0.8 and 0.9) and ARVI (~0.4 and 0.7). The response curve for temperature values exhibited the highest peak among the environmental variables, with a high probability in areas that have a temperature ~28 °C, followed by elevation (~2600 m) and rainfall (~470 mm), respectively (Figure 7).

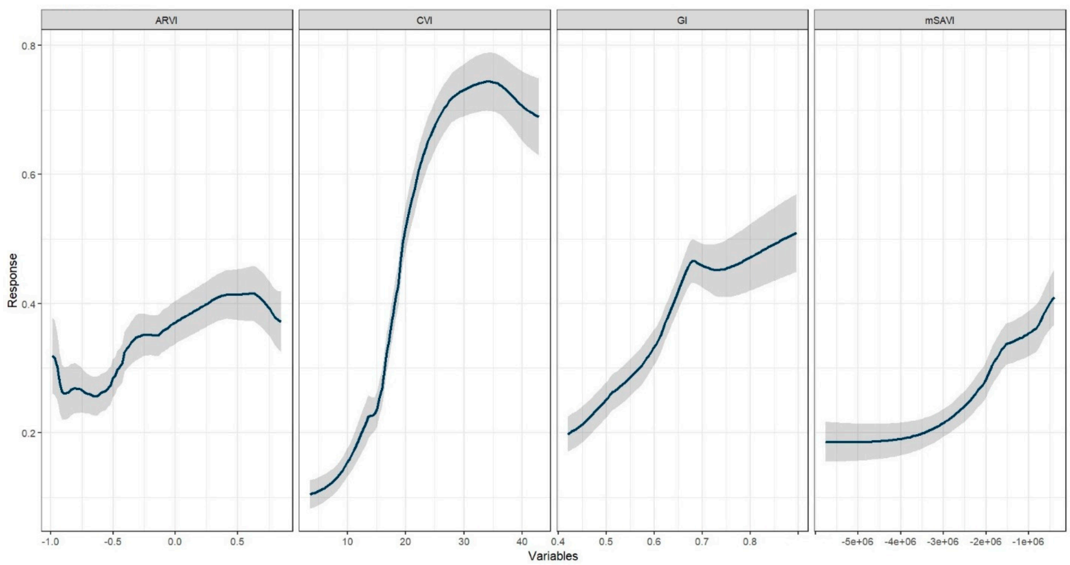

Figure 6. Vegetation index response curve for Acacia *decurrens* presence: blue-black curves show the mean response and gray shades are ±SD calculated through 10 replicate runs in the ensemble model.

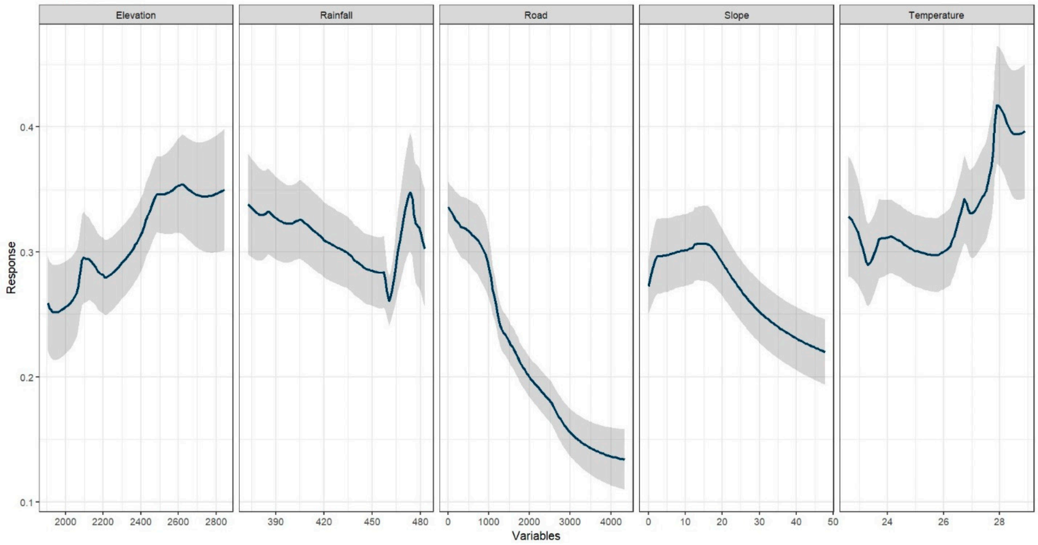

Figure 7. Environmental variable response curve for Acacia *decurrens* presence: blue-black curves show the mean response and gray shades are ±SD calculated through 10 replicate runs in the ensemble model.

4. Discussion

This study modeled the spatial distribution of small-scale Acacia *decurrens* plantation forests, utilizing high-resolution satellite data and environmental variables by employing six different algorithms available in the SDM package.

The assessment of multicollinearity was a crucial phase aimed at identifying and addressing strong correlations among multiple predictor variables used in the identification process. The implementation of the VIF method, recognized for discerning collinearity among predictor variables [78], resulted in the exclusion of almost three-fourths of the total variables due to collinearity issues, potentially decreasing the efficiency of prediction and increasing the uncertainty of the SDM [96]. When VIF exceeds 10, it serves as an indicator of collinearity issues within the model [97]. Furthermore, collinearity represents a significant concern that can potentially result in the incorrect identification of relevant predictor variables [98]. The high correlation among many of the input predictor variables can be attributed to the fact that observations were made within a relatively local scale and due to the similarity in spectral vegetation indices. It is worth noting that all the reduced variables were vegetation indices and raw bands, implying a relatively higher similarity between the generated vegetation indices. This result aligns with the findings of [99], possibly due to the limited spectral resolution of the PS image with only four bands.

The use of a combination of SDM algorithms, such as GLM, MARS, BRT, RF, SVM, and CART, in a complementary manner, along with the incorporation of accuracy estimators based on presence/absence data, enables a more effective representation of the spatial distribution of species at a local scale. The overall accuracy of the algorithms is relatively good, with the values exceeding 0.8 for AUC and 0.6 for TSS (Table 2). Predictive accuracy pertains to the ability of the algorithms to gauge the disparity between observed and predicted values [100]. RF exhibits an AUC above 0.9 and a TSS above 0.8, signifying near-perfect agreement. BRT and SVM demonstrate AUC values above 0.8 and TSS values above 0.7, indicating substantial agreement. The result aligns with the findings of Maxwell et al. [101], who found that machine learning outperformed regression algorithms for species identification. RF attains higher values than other algorithms for both evaluation metrics. This aligns with previous studies that have shown RF's superior performance in species identification [28,102–105], remote sensing image classification [106,107], and data mining [108] compared to other algorithms. This is because the RF algorithm generates predictions by creating thousands of trees and aggregating their results through averaging [86]. This approach allows the algorithm to prevent overfitting, thereby enhancing predictive performance and reducing variance [109]. Thus, RF proves to be a robust technique for modeling species distribution prediction, as supported by previous studies [110–113]. In other studies, it has been noted that generative methods such as RF tend to yield improved results with small sample sizes, possibly due to their faster convergence toward their higher asymptotic error when compared to discriminative methods [114].

The performance of all the applied algorithms was effective, as indicated by the mentioned measures, enabling their inclusion in the ensemble modeling. The spatial extent of Acacia decurrens plantation in the study area was 22.44% during 2022. Worku et al. [63] reported that 17.97% of the district was covered by the plantations during 2017. The proportion of plantations was described as 33.9% in one of the watersheds in the district during 2017 [17]. Another study by Wondie and Mekuria [13] stated that 25.6% of the district was covered by forestlands. The difference in the extent between this study and previous studies might be attributed to differences in the satellite data properties, methodology used, and study time.

The ensemble model unveiled the variable importance and response curves in the prediction of Acacia decurrens distribution. The results indicate that CVI, ARVI, and GI are ranked as the first, second, and third variables, respectively, with values of 39.3%, 16%, and 7.1% based on the AUC metric, signifying the relatively strong influence of vegetation indices. These indices played a predominant role in determining the distribution and proliferation of Acacia decurrens. Vegetation indices played a crucial role in identifying tree species, demonstrating the highest relative importance, and can effectively serve as a classification variable to differentiate evergreen trees [115]. The study by Anna [116] also reported similar variable importance, with vegetation indices being the best predictors of tropical evergreen species. This result is consistent with the description of vegetation index variables exerting a more substantial influence than the bioclimatic variables, significantly contributing to defining the distribution range and landscape patterns in the *Chelodina longicollis* model, with a total contribution of 50.75 compared to 36.94 for the 11 bioclimatic variables [117]. Moreover, Engler et al. [99] also indicated that variables derived from remote sensing are significantly crucial for mapping the spatial distribution of both broadleaved and coniferous tree species at high-resolution data. Elevation, distance to roads, and mSAVI occupy the fourth, fifth, and sixth ranks, respectively, making significant contributions to the species' distribution. Elevation significantly influences the distribution of plant species [118,119], and in particular, the decision of where and whether to establish plantations depends on environmental factors such as elevation [120]. Further, the findings of Altamirano and Lara [121] also indicate that plantation forests tend to be located in areas characterized by moderate elevation levels and a short distance from roads. Rainfall holds the seventh rank in terms of its relative importance in determining the distribution of this species. The lower ranked predictor variables, specifically, temperature and slope, also play a role in the distribution of Acacia *decurrens*. However, in relative terms, they are not as influential as other predictor variables in the model, as indicated by the AUC metrics. This may be attributed to the size of the study area in relation to the resolution of the utilized data.

The response curves in Figure 6 show that the probability of Acacia *decurrens* occurrence generally increases with higher values of vegetation indices. Among the environmental variables, the probability of occurrence increases with higher elevation, keeping other variables constant at their mean value. The probability of occurrence is rare at low-elevation areas of the district because these areas are more suitable for agricultural practices, especially small-scale irrigation activities. This is clearly seen in Figure 7, where the distribution of Acacia decurrens is rare in the Northeastern and Western parts, where small-scale irrigation activities are being carried out along the Guder and Tinbil rivers, respectively. Conversely, the probability of occurrence decreases with an increase in distance from roads and slope (Figure 7). The community cultivates Acacia decurrens to generate income by selling the standing trees or producing charcoal, and road access plays a vital role in facilitating this. Access to roads reduces input costs and in certain situations, leads to higher prices for plantation products [122].

In summary, the findings of this study proved that PS-derived variables and environmental variables integrated with SDM are effective in identifying the distribution of small-scale Acacia *decurrens* plantation forests. This can be attributed to the high spatial resolution of the PS image, suggesting potential applications of PS imagery in small-scale forestry.

5. Conclusions

The Acacia *decurrens* plantation holds significant importance in the study area. Over the past few decades, the rapid expansion of these plantations has brought about both environmental and economic implications. Accurately predicting the spatial distribution of Acacia *decurrens* plantations is essential for concerned authorities to develop effective management policies.

This study successfully employed high-resolution satellite data and advanced techniques to assess the spatial distribution of small-scale Acacia *decurrens* plantation forests. The thorough evaluation of multicollinearity using the VIF method was pivotal, leading to the exclusion of a substantial portion of variables to address collinearity issues, and enhanced the robustness of the SDM. Among the six algorithms utilized, RF emerged as the standout performer, exhibiting near-perfect agreement with AUC above 0.9 and TSS above 0.8. The ensemble model further identified that significant portions of the study area were covered with Acacia *decurrens* plantations and emphasized the critical role of vegetation indices (CVI, ARVI, and GI) in determining its distribution and proliferation, underscoring their high relative importance. This study also revealed that the decision to establish plantations is influenced by environmental considerations such as elevation, with areas of moderate elevation and proximity to roads being favorable for plantation activities. The geographical rarity of Acacia *decurrens* in certain areas was attributed to the prevalence of agricultural practices such as small-scale irrigation.

Ultimately, this research demonstrates the effectiveness of integrating PS imagery-derived variables with environmental factors within SDM, offering valuable insights for identifying and managing small-scale Acacia *decurrens* plantation forests and providing comprehensive information for efficient decision making in land use planning and forestry management at a local scale.

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Appendix A

No.	Name	Abbreviation	Formula
1	Atmospherically Resistant Vegetation Index	ARVI	$\frac{IR-R-y(R-B)}{IR+R-y(R-B)}$
2	Blue Green Pigment Index	BGI	$\frac{B}{G}$
3	Blue Normalized Difference Vegetation Index	BNDVI	$\frac{IR-B}{IR+B}$
4	Chlorophyll Vegetation Index	CVI	$IR\ \frac{R}{G^2}$

No.	Name	Abbreviation	Formula
5	Difference Vegetation Index	DVI	$\mathrm{IR}-\mathrm{R}$
6	Differenced Vegetation Index MSS	DVIMSS	$2.4\mathrm{IR}-\mathrm{R}$
7	Enhanced Vegetation Index	EVI	$2.5\frac{\mathrm{IR}-\mathrm{R}}{(\mathrm{IR}+6\mathrm{R}-7.5\mathrm{B})+1}$
8	Enhanced Vegetation Index 2	EVI2	$2.4\frac{\mathrm{IR}-\mathrm{R}}{\mathrm{IR}+\mathrm{R}+1}$
9	Green Atmospherically Resistant Vegetation Index	GARI	$\frac{\mathrm{IR}-(\mathrm{G}-(\mathrm{B}-\mathrm{R}))}{\mathrm{IR}-(\mathrm{G}+(\mathrm{B}-\mathrm{R}))}$
10	Green-Blue NDVI	GBNDVI	$\frac{\mathrm{IR}-(\mathrm{G}+\mathrm{B})}{\mathrm{IR}+(\mathrm{G}+\mathrm{B})}$
11	Greenness Index	GI	$\frac{\mathrm{G}}{\mathrm{R}}$
12	Green Leaf Index	GLI	$\frac{2\mathrm{G}-(\mathrm{R}-\mathrm{B})}{2\mathrm{G}+(\mathrm{R}+\mathrm{B})}$
13	Green NDVI	GNDVI	$\frac{\mathrm{IR}-\mathrm{G}}{\mathrm{IR}+\mathrm{G}}$
14	Green Optimized SAVI	GOSAVI	$\frac{\mathrm{IR}-\mathrm{G}}{\mathrm{IR}+\mathrm{G}+0.16}$
15	Green-Red NDVI	GRNDVI	$\frac{\mathrm{IR}-(\mathrm{G}+\mathrm{R})}{\mathrm{IR}+(\mathrm{G}+\mathrm{R})}$
16	Green Ratio Vegetation Index	GRVI	$\frac{\mathrm{IR}}{\mathrm{G}}$
17	Infrared Percentage Vegetation Index	IPVI	$\frac{\frac{\mathrm{IR}}{\mathrm{IR}+\mathrm{R}}}{2}(\mathrm{NDVI}+1)$
18	Leaf Area Index	LAI	$3.618EVI-0.118$
19	Modified NDVI	mNDVI	$\frac{\mathrm{IR}-\mathrm{R}}{\mathrm{IR}+(\mathrm{R}-2\mathrm{B})}$
20	Modified Simple Ratio	mSR	$\frac{\mathrm{IR}-\mathrm{B}}{\mathrm{R}-\mathrm{B}}$
21	Modified SAVI	mSAVI	$\frac{2\mathrm{IR}+1-\sqrt{(2\mathrm{IR}+1)^2-8(\mathrm{IR}-\mathrm{R})}}{2}$
22	Normalized Difference Plant Pigment Ratio	PPR	$\frac{\mathrm{G}-\mathrm{B}}{\mathrm{G}+\mathrm{B}}$
23	Normalized Difference Photosynthetic Vigor Ratio	PVR	$\frac{\mathrm{G}-\mathrm{R}}{\mathrm{G}+\mathrm{R}}$
24	Normalized Difference 682/553	ND682/553	$\frac{\mathrm{R}-\mathrm{G}}{\mathrm{R}+\mathrm{G}}$
25	Normalized Difference Vegetation Index	NDVI	$\frac{\mathrm{IR}-\mathrm{R}}{\mathrm{IR}+\mathrm{R}}$
26	Red-Blue NDVI	RBNDVI	$\frac{\mathrm{IR}-(\mathrm{R}+\mathrm{B})}{\mathrm{IR}+(\mathrm{R}+\mathrm{B})}$
27	Renormalized Difference Vegetation Index	RDVI	$\frac{\mathrm{IR}-\mathrm{R}}{\sqrt{\mathrm{IR}+\mathrm{R}}}$
28	Soil Adjusted Vegetation Index	SAVI	$\frac{\mathrm{IR}-\mathrm{R}}{\mathrm{IR}+\mathrm{R}+L}(1+L)$
29	Simple Ratio	SR	$\frac{\mathrm{IR}}{\mathrm{R}}$
30	Transformed NDVI	TNDVI	$\sqrt{\frac{\mathrm{IR}-\mathrm{R}}{\mathrm{IR}+\mathrm{R}}+0.5}$
31	Weighted Difference Vegetation Index	WDVI	$\mathrm{IR}-\alpha\mathrm{R}$
32	Wide Dynamic Range Vegetation Index	WDRVI	$\frac{0.1\mathrm{IR}-\mathrm{R}}{0.1\mathrm{IR}+\mathrm{R}}$

where B is blue band, G is green band, R is red band, IR is infrared band, α is 0.2, and L is 0.5.

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