Modeling and Mapping Habitat Suitability of Highland Bamboo under Climate Change in Ethiopia

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Abstract: Highland bamboo (Oldeaania alpina formerly Arundinaria alpina or Yushania alpina) is a species of significant conservation value in Afromontane ecosystems across Africa. It also plays a significant role in the livelihoods of local communities. However, global climate change is anticipated to alter its ecological niche, leading to range shifts and possible habitat contractions. This study aimed to identify potentially suitable habitats for highland bamboo in Ethiopia, determine the resilience of the species under climate change, and establish the environmental factors affecting its habitat. Species distribution modeling (SDM) was implemented in the SDM R package using 231 georeferenced presence records together with climate, topographic, and soil data. To assess climate change risks to the species, predictive models were developed assuming climate scenarios for 2061–2080 under two shared socio-economic pathways (SSPs), namely, SSP2-45 and SSP5-85. The results indicated that highland bamboo mainly grows in high elevation areas with altitudes of 2100–3100 m asl with mean annual temperatures of 11.5–19.3 °C, annual precipitation of 873–1962 mm, precipitation of the driest quarter of 36–147 mm, soil pH of 5.6, and soil CEC of 30.7 cmolc/kg. The current potentially suitable habitat for this species in Ethiopia was estimated at 61,831.58 km², with the majority of habitats being in the southern and southwestern parts of the country. Our models predicted that the suitable habitat will shrink by 13.4% under the SSP5-85 scenario, while potential new suitable areas for this species were identified under the SSP2-45 scenario. Future vulnerable areas were mostly found in central Ethiopia. Based on the predictions, we conclude that most of the suitable habitats for highland bamboo will remain suitable between the years 2061 and 2080.

Keywords: Afromontane; Arundinaria alpina; ensemble model; species distribution modeling; Yushania alpina

1. Introduction

Africa is anticipated to experience substantial climatic changes through the 21st century [1,2]. According to Christensen et al. [3], regions across Africa will face temperature rises of 3–4 °C, which are approximately 1.5 times higher than the global mean, between 2080 and 2099. At the end of the century, sub-Saharan Africa is predicted to experience mean annual temperatures of 26.4–27.6 °C for RCP4.5 and 27.9–29.8 °C for RCP8.5 [4].
Warming has been prevalent in most parts of Ethiopia at different levels, since the 1970s, which is broadly consistent with the wider African and global trends [5]. According to historical data, average annual temperatures rose by 1.3 °C during 1960–2006, or at an average rate of 0.28 °C per decade [6]. Depending on the emission scenarios, annual temperatures are also projected to rise by 1.1–3.1 °C by the 2060s and 1.5–5.1 °C by the 2090s [7]. As anthropogenic climate change remains, the threats to biodiversity will intensify over time, with a likely disastrous loss of global biodiversity being imminent [8].

The distribution and abundance of most species are likely to be affected by changes in atmospheric CO₂ and climate [2]. If the increases in global average temperature exceed 1.5–2.5 °C, 20–30% of plant and animal species are likely to be at an increased risk of extinction [9]. Major changes are also expected in ecosystem structure and function, ecological interactions, and the geographical ranges of species. This will have predominantly negative consequences for biodiversity and ecosystem goods and services. Endemic species with restricted geographic ranges may be particularly vulnerable [10]. According to McClean et al. [11], over 5000 African plant species are expected to lose their climatically suitable habitats by 2085. Conway and Schipper [5] identified Ethiopia as one of the extreme examples of vulnerability to climate change.

An imperative for ecologists now is to understand the processes regulating species distribution and identify the influential environmental factors that are likely to determine the changes in distribution [12]. Predicting habitat suitability of species is fundamental for establishing nature reserves or cultivating suitable regions for economically important and vulnerable plant species. Species distribution modeling (SDM) aims to predict areas where environmental conditions are appropriate for the survival of a species, even where a given species is not currently appearing, which is called the potential distribution or fundamental niche [13]. SDMs are important for predicting species distributions, evaluating climate sensitivity and possible climate change impacts on plant species, identifying populations that are vulnerable, and identifying areas where urgent conservation measures are needed [14,15].

Among the taxa most vulnerable to reductions in suitable habitat due to climate change are those that are adapted to Afromontane (Afroalpine) forest ecosystems [16]. Afromontane forests constitute a unique forest type occurring on high mountains extending from Ethiopia in the east to Cameroon in the west and South Africa in the south [17–19]. Although they are widely separated, they share a similar mix of over 4000 plant species (~3000 species are endemic), which are often distinct from the surrounding lowland forests [19]. Afromontane forests are among the major natural forest types in the highlands of Ethiopia [20]. Being the remnant forests in different parts of the country, these forests have great ecological significance providing habitats for many endangered species. Many of the Afromontane species are Ethiopia’s flagship species [21].

Afromontane forest ecosystems are likely to be sensitive to global warming owing to the reduction in areas with increasing elevation. According to a recent global assessment, Afromontane species will experience unprecedented rates of warming during the 21st century, 2–3 times greater than those observed during the 20th century [22]. One such species is the highland bamboo *Oleandria alpina* (K. Schum) Stapleton (formerly *Arundinaria alpina* or *Yushania alpina*). It occurs mostly on high mountains [23], which are some of the most essential water towers in Africa. Highland bamboo is limited to elevations of 2000–4000 m [23], but it is a conspicuous element of the vegetation of most East African mountains, including the Ethiopian highlands, southern highlands of Tanzania, and Malawi [24]. It also appears on the Bamenda Mountains of Cameroon [24]. This species forms huge pure stands providing important habitats and food for wildlife on the high mountains of significant conservation status in Africa, including Mt. Kivu in Zaire, the Virunga transboundary protected area in the Democratic Republic of Congo (DRC), Uganda and Rwanda [25], the Aberdares and Mau ranges and Mt. Kenya in Kenya, the highlands of Ethiopia, Mt. Uluguru in Tanzania, Mt. Mulanje in Malawi, and Mt. Cameroon in Cameroon [25,25,26]. In the Virunga transboundary protected area, highland bamboo provides important habitat
and food for the critically endangered eastern Mountain Gorillas [25,26] and African golden monkeys. The bamboo shoots account for 90% of the gorilla diet and 60% of the food for golden monkeys in certain periods of the year [25]. In Kenya, highland bamboo provides habitat for the endangered (IUCN Red list) mountain bongo in the Aberdare Mountains. Therefore, the conservation of highland bamboo forests on mountains is critical for the protection of the remnant populations of these endangered species.

In Ethiopia, highland bamboo is an ecologically and economically important indigenous species with a narrow ecological range. Nevertheless, natural regeneration is usually hampered due to human interference, mass flowering, and climate change [27,28]. The anticipated changes in climate have the potential to change the current distribution of this species. Understanding its distribution under climate change will be useful to inform policy makers to devise robust conservation strategies for the long-term persistence of this species. Therefore, the objectives of this study are (1) to determine the current potential distribution of highland bamboo, (2) to predict its future suitable habitats under climate change scenarios, and (3) to identify key climate variables that determine habitat suitability to aid conservation efforts in Ethiopia. Although this study focused on Ethiopia, the results are hoped to be relevant to other countries where highland bamboo occurs.

2. Materials and Methods

2.1. Study Area

The study was conducted in highland bamboo growing areas across Ethiopia (Figure 1). Bamboo covers an estimated area of approximately 14,744.63 km$^2$ in Ethiopia [29]. The total area of highland bamboo in Ethiopia is estimated to be 1486.26 km$^2$, of which 1296.26 km$^2$ is naturally growing, while 190 km$^2$ is planted by farmers [30]. Most of the highland bamboo resources are found in the southern and central parts of Ethiopia, mainly in Oromia and the Southern nations, nationalities, and people’s regional states. Most of the countries’ highland bamboo is found in the Bale Mountains, which accounts for an area coverage of approximately 78.36 km$^2$ [31].

Figure 1. Highland bamboo occurrence data collection locations.
2.2. Geospatial data

2.2.1. Species Occurrence Data Collection and Processing

Inventories and occurrence data were collected across the entire highland bamboo growing areas of Ethiopia (Figure 1). In total, 231 well-defined species presence data points were collected from field observations and specimen records of the species from the National Herbarium of Ethiopia, Addis Ababa University (Table S1). Metadata including specimen number, species name, date of collection, and georeferenced coordinate pairs as decimal latitude–longitude were retrieved. Most SDM methods require the involvement of occurrence data to be spatially independent to achieve good performance. The exclusion of spatial clusters of localities is essential for model calibration and evaluation. The presence of spatial clusters of localities usually makes models overfit to environmental biases (reducing the model’s capacity to predict spatially independent data), and model performance values become overestimated [32,33]. Spatial autocorrelation in species occurrences interferes with independence between the test and training data sets if the division of the training and test data is executed randomly [13]. Thus, we employed the Spatially Rarefy Occurrence Data Tool in the SDM toolbox of ArcGIS 10.3 [34] to filter multiple occurrence points found within a 1 km$^2$ grid and to reduce to a single point [33]. This left 129 highland bamboo presence points to build the final SDM.

2.2.2. Predictor Environmental Variables

Predictor variables were carefully selected to ensure that the models were appropriate for the studied species. The current and future potential distribution areas of highland bamboo were based on the species’ environmental niches that were derived from current environmental data [14]. A total of 24 environmental variables were examined in our model to understand the current climate requirements of highland bamboo and to predict current potential habitats and plausible future suitable niches across the landscape of Ethiopia until 2099 (Table 1). Of these, 19 bioclimatic variables were taken from the WorldClim 2.1 data set [35], 2 topographic variables (slope and aspect) were taken from USGS Digital Elevation-Shuttle Radar Topography Mission (https://www.usgs.gov) (accessed on 29 January 2022), and 3 soil variables (soil texture, soil pH, and soil CEC) were taken from ISRIC—World Soil Information (https://www.isric.org) (accessed on 9 February 2022).

The bioclimatic variables were extracted from worldwide monthly temperature and rainfall records. The variables are usually used in ecological niche modeling to produce better biologically significant variables [36]. The data sets are generated by interpolation of observed climate data (9000 to 60,000 weather stations) between 1970 and 2000 and are at a resolution of 30 arc-sec (nearly 1 km at the equator) [35]. Compared to the former version, WorldClim 2.1 prediction accuracy for temperature variables is increased by 5–15% (0.07–0.17 $^\circ$C) due to remote sensing data [37]. All the environmental layers were kept in raster format with similar cell sizes and reference systems to be appropriate for SDM. The data were then clipped to our study area and converted to ASCII using ArcGIS [38]. The key environmental variables that affect the habitat suitability of highland bamboo were determined according to their contributions to the modeling process.

The models used in this study were the third Hadley Centre Global Environmental Model run in the Global Coupled configuration 3.1 (HadGEM3-GC31-LL) [39], the Goddard Institute for Space Studies Model version E2.1-H (GISS-E2-1-H) [40], and the second generation Euro-Mediterranean Centre on Climate Change Earth System Model (CMCC-ESM2) [41]. The models are downscaled global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) [42]. The models were selected owing to their better performance in the Ethiopian environment [43–45] and dissimilarity (to reduce interdependence) [46]. For the models, two shared socio-economic pathway (SSP) scenarios (SSP2-45 and SSP5-85) at the end of the century (average for 2061–2080) were examined. SSP2-45 and SSP5-85 project global temperature anomalies of 2.4 $^\circ$C and 4.9 $^\circ$C above pre-industrial levels by 2100 with atmospheric CO$_2$ equivalents of 650 and 1370 ppm, respectively [4,47,48].
Table 1. Realized niches of highland bamboo.

| Code | Environmental Variable                        | Mean    | Minimum | Maximum |
|------|-----------------------------------------------|---------|---------|---------|
| Bio_1 | Annual mean temperature                      | 14.81   | 11.54   | 19.33   |
| Bio_2 | Mean diurnal range                           | 13.07   | 11.09   | 15.61   |
| Bio_3 | Isothermality                                 | 80.57   | 75.25   | 86.19   |
| Bio_4 | Temperature seasonality                       | 93.76   | 49.78   | 134.35  |
| Bio_5 | Max temperature of warmest month             | 22.46   | 18.90   | 27.50   |
| Bio_6 | Min temperature of coldest month             | 6.22    | 3.60    | 9.80    |
| Bio_7 | Temperature annual range                     | 16.24   | 13.50   | 18.60   |
| Bio_8 | Mean temperature of wettest quarter          | 14.10   | 10.95   | 18.60   |
| Bio_9 | Mean temperature of driest quarter           | 15.00   | 11.57   | 20.65   |
| Bio_10 | Mean temperature of warmest quarter          | 15.97   | 12.05   | 20.93   |
| Bio_11 | Mean temperature of coldest quarter          | 13.71   | 10.57   | 18.50   |
| Bio_12 | Annual precipitation                          | 1443.89 | 873.00  | 1962.00 |
| Bio_13 | Precipitation of wettest month               | 237.68  | 146.00  | 329.00  |
| Bio_14 | Precipitation of driest month                | 29.32   | 12.00   | 39.00   |
| Bio_15 | Precipitation seasonality                    | 63.73   | 46.35   | 114.47  |
| Bio_16 | Precipitation of wettest quarter             | 635.36  | 364.00  | 1094.00 |
| Bio_17 | Precipitation of driest quarter              | 91.40   | 36.00   | 147.00  |
| Bio_18 | Precipitation of warmest quarter             | 286.57  | 139.00  | 496.00  |
| Bio_19 | Precipitation of coldest quarter             | 518.21  | 41.00   | 1089.00 |

Elevation (m) 2539 1595 3097

Slope (%) 4 0 16

Aspect (degree) 197 5 357

Soil_pH 5.6 5 6.6

Soil_cic Soil Cation Exchange Capacity (cmolc/kg) 30.7 22 47

Soil_tex Soil texture - - -

Temperature is given in °C and precipitation in mm.

2.2.3. Variable Correlation Analysis

To ascertain a set of independent variables and to minimize model over parameterization [49,50], very correlated climatic variables were omitted from further analysis. The USDM R package was used to produce the correlation matrix of the climatic variable [51]. All variables beyond a threshold value were withdrawn from the analysis following a VIF step procedure.

2.3. Analysis of Realized Niche

The realized niche of highland bamboo was identified based on the current species occurrence points and corresponding environmental data following Scheldeman and Zonneveld [14]. The environmental data of the respective highland bamboo presence sites were extracted using ArcGIS 10.3 [34]. The data were then further analyzed and visualized in Excel spreadsheets.

2.4. Distribution Modeling and Model Performance Evaluation

Various methods are available for fitting SDMs [52] differing in their predictive power and ability to detect different numbers of important predictors [53,54]. We compared the performance of six modeling approaches, namely, Generalized Linear Models (GLMs), Maximum Entropy (MaxEnt), Boosted Regression Trees (BRT), Random Forest (RF), Support Vector Machines (SVM), and Multivariate Adaptive Regression Splines (MARS). We evaluated model discrimination ability using true skill statistic (TSS), Kappa, area under the curve (AUC) of the receiver operator characteristic (ROC), and the deviance statistic. These measures attribute different weights to the various types of prediction errors [55]. AUC is an effective, threshold-independent indicator. AUC values below 0.7 were considered poor, 0.7–0.9 moderate, and >0.9 good [56]. Although the Kappa statistic is the most widely used, several studies have criticized it for being inherently dependent on prevalence. The TSS corrects for this dependence while still keeping all the advantages of
kappa [55]. Both Kappa and TSS are threshold-dependent measures of model accuracy [56] and their values ranged from $-1$ to $+1$, where $+1$ indicates perfect agreement between predictions and observations, and values of 0 or less indicate agreement no better than random classification [56]. The following ranges were used to interpret Kappa and TSS statistics: values < 0.4 were poor, 0.4–0.8 useful, and > 0.8 good to excellent.

Ensemble forecasting is advocated because this approach is expected to balance the accuracy and robustness of SDM models [56]. To reduce uncertainty in species distribution projections, in this analysis, the simple average consensus approach was used to combine the ensemble model. We chose one ensemble model from the weighted means of better-performing models based on the criteria in Table 2. We then used the selected model to predict the habitat suitability of the highland bamboo. To evaluate the predictive ability of the models, we used both bootstrap and subsampling replication approaches [57]. The randomly selected points were split into two sets so that the model was calibrated using 70% of the training data set and 30% of the test data set. We performed all modeling using the SDM R package [57].

Table 2. Performance evaluation of SDMs using different statistical parameters.

| Methods  | AUC   | TSS   | Kappa  | COR   | Deviance |
|----------|-------|-------|--------|-------|----------|
| GLM      | 0.97  | 0.89  | 0.84   | 0.88  | 0.78     |
| MAXENT   | 0.99  | 0.95  | 0.91   | 0.92  | 0.53     |
| BRT      | 0.99  | 0.94  | 0.91   | 0.92  | 0.59     |
| RF       | 0.99  | 0.94  | 0.92   | 0.93  | 0.24     |
| SVM      | 0.98  | 0.91  | 0.91   | 0.92  | 0.32     |
| MARS     | 0.96  | 0.90  | 0.84   | 0.87  | 3.48     |
| Ensemble | 1.00  | 0.96  | 0.96   | 0.95  | 0.36     |

2.5. Spatial Characterization of Highland Bamboo

The distribution map outputs from the ensemble model were imported into ArcGIS 10.3 [34] and suitability classification, as well as visual interpretation, were performed by employing spatial analysis tools such as overlay analysis [12]. Visualization was enhanced by adjusting the standard legend to a gradual scale. The maximized sum of sensitivity and specificity (equivalent to maximizing TSS) was used to generate binary presence–absence predictions [44,57]. Distribution maps were developed as pixels greater than the threshold represented the presence of highland bamboo and pixels lower than the threshold indicated the absence of the species [58]. A new class ranging from zero (0) to the threshold value was generated, and a neutral color was assigned for this new class. An administrative unit layer was included to enable locating the potential distribution areas [14].

Investigation of climate change impact was evaluated by first generating a potential distribution map for highland bamboo with current climate data and then creating a potential distribution map for the species under future climate scenarios. Subsequently, an overlay analysis was performed from the potential current suitable areas map to the potential future suitable areas map for highland bamboo using a GIS environment. Four possible circumstances were identified for each cell using overlay analysis [14]:

1. High impact areas—areas where a species potentially appears in the present climate but will no longer be suitable in the future;
2. Areas outside of the realized niche—areas that are neither suitable under current conditions nor under future conditions;
3. Low impact areas—areas where the species can potentially exist in both present and future climates;
4. New suitable areas—areas where a species could potentially exist in the future, but which are not suitable for natural occurrence under current conditions.
3. Results

3.1. Correlation between Environmental Variables

Ten variables from the twenty-four input variables had a collinearity problem and were removed from the analysis. These variables were bio_6, bio_10, bio_7, bio_1, bio_5, bio_16, bio_11, bio_13, bio_17, and bio_9. Therefore, we reduced the environmental variables to 14, for use in our modeling to map the distribution of highland bamboo. After excluding the collinear variables, the linear correlation coefficients ranged between a minimum correlation (bio_4~bio_3) of 0.01 and a maximum correlation (soil_tex~bio_2) of −0.61.

3.2. Realized Niche of Highland Bamboo

Environmental variables influencing the realized niche of highland bamboo are presented in Table 1. The lowest altitude favorable for growing the species was observed at Dawro (2095 m asl), and the highest altitudinal elevation was observed in the Gurage Highland (3097 m asl). The mean distributional elevation was found to be 2539 m asl.

3.3. Model Performance

Most of the models predicted the distribution of highland bamboo fairly accurately, with the RF and MAXENT performing best, while the performance of the MARS and GLM methods was relatively poor (Table 2 and Figure S1). Thus, the final prediction was made with the ensemble of only RF, MAXENT, BRT, and SVM models. The ensemble model achieved a higher discriminative ability with an overall AUC, TSS, and Kappa of 1, 0.96, and 0.96, respectively (Table 2).

3.4. Variable Importance Analysis

The different methods identified different variables as important, which gave widely differing variable importance plots (Figure S2). Relative variable importance analyzed by the ensemble model indicated that the key environmental factors that had a determining influence on the suitable geographical distribution of highland bamboo were mean temperature of the wettest quarter (bio_8), annual precipitation (bio_12), precipitation of driest month (bio_14), Isothermality (bio_3), soil pH, and soil CEC. The remaining environmental variables have relatively lower influences in determining the fundamental niche of the species (Figure 2). Aspect and slope contributed the least to the model.

Figure 2. Relative contributions of environmental variables based on the ensemble modeling of the distribution of highland bamboo.
3.5. Present and Future Distributions of Highland Bamboo

The vast majority of predicted suitable habitats for highland bamboo under current climate conditions lie within the West Shewa, Arsi, Shaka, Kaffa, Jimma, Gamo Gofa, Gedeo, Guji, Sidama, Bale, Hadiya, Guraghe, Kembata, Dawuro, East Wellega, Awi, and Illubabor administrative areas. The habitat suitability projections of highland bamboo across Ethiopia under the current climate showed major suitable areas beyond the realized niche of the species. Under future climate scenarios, the species is predicted to retain most of its potential habitat in both scenarios (Figure S3). The probabilistic distribution of highland bamboo in Ethiopia produced by the ensemble model is depicted in Figures 3–5.
The threshold value produced by ensemble model analysis for highland bamboo was found to be 0.5. This value indicates the minimum probability of suitable habitat distribution of the species. Accordingly, a total of 61,831.58 km² (6,183,158 ha) of land is estimated to be a potentially suitable habitat for highland bamboo in Ethiopia. This constitutes approximately 5.5% of Ethiopia’s total land area. The current predicted area outside the fundamental niche of highland bamboo in Ethiopia is approximately 1,063,559 km². The predicted amount of future suitable habitat for highland bamboo with medium forcing scenario (SSP2-4.5) and strong forcing scenario (SSP5-8.5) is estimated at 72,490 and 53,553 km², respectively.

Regions included as suitable areas for highland bamboo under the future climate scenarios included the West Shewa, Arsi, Shaka, Kaffa, Jimma, Gamo Gofa, Gedeo, Guji, Sidama, Bale, Hadiya, Guraghe, Kembata, Dawuro, East Wellega, Awi, and Illubabor administrative areas. Certain areas of Bale, Awi, and Illubabor provinces are interestingly predicted to have newly suitable areas for growing highland bamboo and, thus, provide a baseline for introducing the species into those areas in the future.

![Figure 5. Predicted habitat suitability of highland bamboo in Ethiopia under future condition, SSP5-85 scenario, from the mean of the three GCMs.](image-url)

Some places within the present fundamental niches were found to be not conducive habitats for highland bamboo species in the future (high impact areas). This was the case for East Wellega, Arsi, and parts of West Shewa administrative areas. The Somali, Afar, Gambela, Benshangul-Gumaz, Dire Dawa, Harari, Tigray, Harerghe, Borena, and most of the Amhara region of the country are not suitable habitats for highland bamboo in either current or future predictions (areas outside of the fundamental niche). The study revealed that most of the current potential growing areas for highland bamboo remain suitable habitats in future climate scenarios.

### 3.6. Overlay Analysis of Current and Future Potential Distribution Areas

Situation analysis performed by overlaying the current and future potential distribution areas produced four possible situations (Figures 6 and 7). The extent of areas for the four situations for both scenarios is presented in Table 3.
Figure 6. Impact of climate change on habitat niche suitability of highland bamboo under medium forcing scenario (SSP2-4.5).

Table 3. Situational analysis of the impact of climate change on the distribution of highland bamboo.

| Situations                           | Amount of Land (km²) |
|--------------------------------------|----------------------|
|                                      | SSP2-45              | SSP5-85              |
| High Impact on Highland Bamboo      | 4862.01              | 11,727.55            |
| Low Impact on Highland Bamboo       | 55,402.19            | 48,537.52            |
| Potential New Suitable Areas        | 15,208.97            | 3617.83              |
| Areas Outside of the Realized Niche | 1,057,786.06         | 1,069,377.20         |
Figure 7. Impact of climate change on habitat niche suitability of highland bamboo under strong forcing scenario (SSP5-8.5).

4. Discussion

To rehabilitate, conserve, develop, and utilize a species in an ecosystem, comprehensive knowledge of its distribution is usually imperative [12]. Many studies on SDM have tried to determine the realized niche; the greater the realized niche resembles the fundamental niche, the better the projections are plausible. When SDM models are based on bioclimatic factors, the projections tend to be a fundamental niche, especially for new places and future predictions [59]. In Ethiopia, very few studies have been conducted to study the impact of climate change on species distribution using SDM, such as [49,50,59–63]. Using ensemble forecasting approaches, here we present the distribution of highland bamboo in Ethiopia. We believe our methodology and the results can be applied for the conservation and sustainable utilization of this species in Ethiopia and elsewhere in Africa where it occurs.

4.1. Highland Bamboo Niches

A realized niche represents a set of all environmental conditions that allow a species to survive in the existence of competitors or other adversely interacting species and limiting factors [64]. According to the findings from this study, highland bamboo prefers to grow in higher elevation regions with altitudes of 2100–3100 m asl. This result is consistent with previous references and studies on highland bamboo [23,31,65,66].
temperature and annual precipitation requirement for highland bamboo ranged from 11.54 to 19.33 °C and 873 to 1962 mm, respectively, which is inconsistent with previous studies [23, 67]. The species was found to be well adapted in areas receiving a Mean Temperature of Warmest Quarter (12.05–20.93 °C), Precipitation of Driest Month (6–39 mm), and Precipitation of Driest Quarter (36–147 mm). In summary, an interaction between temperature and precipitation will influence the habitat requirements of highland bamboo.

Thus, the results of this study indicated that highland bamboo is restricted to upland areas and occurs mainly in cool growing conditions where there is enough precipitation. These ecological factors can meet the habitat requirements of highland bamboo and provide theoretical references for effective habitat restoration, conservation, development, and resource utilization of the species.

4.2. Suitable Habitat for Highland Bamboo under Current Climate Conditions

Analyzing the potential distribution of a species under current bioclimatic conditions is an essential part of better management and conservation of a species [13]. Representing the spatial distribution of bamboo is crucial for resource utilization, ecosystem provision management, and biodiversity conservation [29]. Predicting potentially suitable habitats for highland bamboo in current climate situations is important to ascertain new habitats for enhanced development and utilization of the species.

Our study revealed the presence of extensive areas in the country where bamboo species may potentially occur. The predicted present distribution is consistent with the evidence from the literature, herbarium records, and field occurrence records [31, 65, 66]. The predicted potential habitat for growing highland bamboo (6,183,158 ha) is much higher than the estimated area occupied by the species in the country, which is approximately 148,626 ha, in earlier reports [30]. Nevertheless, highland bamboo may not necessarily occupy all the potential areas represented by the model because species dispersal is limited by its reproductive system and the presence of geophysical barriers [13]. Thus, the combination of information from species distribution modeling, scientific literature, and expert data will help to provide a complete picture of the natural distribution of a given species [14].

In Africa, highland bamboo is found in the mountains of Uganda, Kenya, Tanzania, Cameroon (Mt. Cameroon), Malawi (Nyika Plateau), Zaire (Kivu), Rwanda, Burundi, and Sudan [66]. The species is restricted to the sub-Saharan region, endemic to Africa, and indigenous to Ethiopia [68]. Highland bamboo naturally grows in the central, south, southwest, and northwest highlands of Ethiopia, commonly on volcanic soils as vast pure stands [66, 68].

4.3. Predictions under Different Climate Scenarios and Impact of Climate Change on the Distribution of Highland Bamboo

Future predictions of habitat suitability by employing SDMs should consider assumptions and uncertainties associated with it since projecting future climate with high confidence is impractical. Applications and uses of SDMs for estimating range shifts and sensitivity to the extinction of a species to climate change, however, are inevitable [14, 59].

The estimated potential future distributions of highland bamboo were different depending on the greenhouse gas emission scenarios used in the model. Nevertheless, in both medium and high forcing scenarios, there were profound projected outcomes as the century progresses. The model forecasts that in the studied time span (2061–2080), the current highland bamboo niche suitability of Ethiopia could decline in size by 8278 km$^2$ for the SSP5-85 scenario, if no interventions are made. This is likely due to a decline in the area available and its suitability for highland bamboo at higher elevations as temperatures increase. Climate change will particularly affect highland bamboo populations in high-impact areas in the future, and local extinction is the likely consequence [2,13]. On the contrary, the species suitable habitat will increase by 10,658 km$^2$ under the SSP2-45 scenario. This is probably related to the creation of new suitable habitats for the species as favorable environmental conditions will exist.
Similar studies conducted for bamboo and other species in Ethiopia and globally [13,59,60,69,70] also revealed a future habitat range reduction and shifts owing to the impact of climate change. Likewise, the results indicated that if climatic factors such as precipitation and temperature variation in a region exceed the tolerance of a species, then range shifts in the species may be certain [13,71]. However, SDMs may exaggerate climate change impacts on species distribution, as species can have the ability to adjust themselves to a range of environments. The influence of competition, predators, soil conditions, and other factors on species potential distribution and likely future shifts should also be noted [14].

4.4. Potential Sites for Conservation of Highland Bamboo

Regions predicted to remain suitable for growing highland bamboo in the future in both scenarios (Shaka, Kaffa, Jimma, Gamo Gofa, Gedeo, Guji, Sidama, Bale, Hadiya, Guraghe, Kembata, Dawuro, Awi, and Illubabor) could be considered potential areas for high-priority conservation [2]. Kaffa, Shaka, Awi, and Sidama have the most inherent resilience, mainly due to the potential for the highland bamboo niche to improve suitability at higher elevations [59]. Future vulnerable highland bamboo growing places in Ethiopia included the Arsi, West Shewa, East Wellega, and East Gojam administrative areas. In essence, these areas may be ranked when establishing conservation plans, such as the collection of germplasm, to ensure the ex situ conservation of genetic resources before climate change will abandon the existing populations. Moreover, an in situ conservation plan might be essential to conserve highland bamboo populations in low-impact areas and expected newly suitable areas, where models predict that the species will survive in the future, protecting them from encroachment [14]. Places that were predicted to have suitable habitat in both the present and the future but not actually observed to have highland bamboo cannot be considered potential areas for conservation of the species [2].

5. Conclusions

Using ensemble modeling, this study determined the distribution of highland bamboo in Ethiopia and provided novel information on the resilience of the species to climate change impacts. The main climatic factors that influence the habitat suitability of highland bamboo are mean temperature of the wettest quarter, annual precipitation, precipitation of the driest month, Isothermality, soil pH, and soil CEC. It is concluded that the potentially suitable habitat for highland bamboo in the country is much more than what is currently occupied by the species. The southwestern and southern highlands of the country are highly suitable for highland bamboo. It is also concluded that most of the suitable habitat for highland bamboo in Ethiopia was predicted to remain towards the end of the century. Potential growing areas in the Arsi and parts of West Shewa and East Wellega administrative areas will be the most susceptible under projected climate change scenarios. Shaka, Kaffa, Jimma, Gamo Gofa, Gedeo, Guji, Sidama, Bale, Hadiya, Guraghe, Kembata, Dawuro, Awi, and Illubabor were identified as climatically suitable areas under both scenarios. There are also places found to be new suitable habitats for highland bamboo in Ethiopia in the future. These include parts of the Bale, Awi, and Illubabor areas. Predicted suitable habitats of highland bamboo contribute substantially to our understanding of the distribution, and potential growing and conservation areas of the species. The results of this study have practical applications such as rehabilitation of highland bamboo habitats and conservation and sustainable utilization of this species not only in Ethiopia, but also in Afromontane forests elsewhere in Africa. However, detailed research is needed to verify whether highland bamboo can be established in potentially suitable habitats where it is not currently observed. The current finding is based on the multi-model mean of three GCMs. We recommend further study on the impact of climate change in highland bamboo growing areas across Africa with all the four shared socioeconomic pathways and future time periods.
Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.390/f13060859/s1, Table S1: Highland bamboo occurrence data points (231) in Ethiopia, Figure S1: Receiver operating characteristic, Figure S2: Relative variable importance. Figure S3: Predicted habitat suitability of highland bamboo in Ethiopia under future conditions at different global climate models (GCMS) and shared socio-economic pathways (SSPs).

Author Contributions: Conceptualization, D.Y. and S.N.; methodology, D.Y. and W.Z.; investigation, D.Y.; writing—original draft preparation, D.Y.; writing—review and editing, D.Y., S.N., B.T.H., W.Z., G.W.S., R.L.R. and T.M.W.; visualization, D.Y. and B.T.H.; funding acquisition, D.Y., T.M.W. and R.L.R. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Addis Ababa University; Ethiopian Environment and Forestry Research Institute; and Forest Sector Development Program of the UNDP/MEFCC.

Data Availability Statement: The bioclimatic variables are available from the WorldClim-Global Climate Database (http://worldclim.org/) (accessed on 25 January 2022).

Acknowledgments: The authors are sincerely thankful to the Ethiopian Environment and Forest Research Institute (EEFRI) for providing transport facilities to conduct the research work. The authors acknowledge the financial support from EEFRI and Addis Ababa University. The authors also acknowledge technical support from Nurhussen Ahmed.

Conflicts of Interest: The authors declare no competing interests.

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