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Modeling impacts of climate change on the geographic distribution and abundances of *Tamarindus indica* in Tigray region, Ethiopia

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ABSTRACT

Tamarindus indica is a multipurpose dry land species in sub-Saharan that is traditionally used to build resilience into the farming system. The species is highly threatened and listed on the IUCN Red List. However, information on how climatic condition locally influences its ecological distribution is limited. This study investigates the current and future suitable habitat for the species in the Tigray region, in northern Ethiopia. A total of 220 species presence points and the number of *T. indica* within a 50 m × 50 m plot were collected. In addition, 19 bioclimatic variables, 3 topographic variables and soil data were used to model the impact of future climate conditions under two Representative Concentration Path Ways (RCP4.5 and RCP 8.5). MaxEnt-v-3.3.3 k, Diva-GIS-7.5, and GIS10.6 were used to model the current and future distribution. SPSSv-26 was also utilized to analyze the relationship between the species' abundance and environmental variables. Results showed that the environmental variables determining most for the distribution of *T. indica* were mean diurnal range (Bio2 (56.9%)); temperature seasonality (Bio4 (10.3%)) and temperature annual range (Bio7 (9.2%)). The model suggested that the current distribution of *T. indica* covers an area of 9209 km^2 (14.04%). This would have increased to 29,363 km^2 (44.78%) and 11,046 km^2 (16.85%) by 2070 under RCP4.5 and RCP8.5, respectively. Compared to the high-impact areas, new gains of suitable areas (net 25,081 km^2) for the future distribution of the species were predicted in 2070-RCP4.5. Altitude, rainfall, temperature, silt contents of soils and soil pH have significant contributions (P-value<0.05) to the abundance of *T. indica*. However, altitude has a negative relationship with the abundance of *T. indica*. Additional studies to understand population trends and other threats are recommended.

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1. Introduction

Forests and woodlands provide a wide range of ecosystem services to people living in both developed and low-income countries [1]. Despite such profound benefits they are being threatened because of various anthropogenic factors. Deforestation resulting from agricultural expansion and climate change are putting the distribution and coverage of forests and woodlands at risk [2,3]. The increase of world's temperature over time leads to an increment in desert-like dry conditions that will affect not only the survival of certain species, but also pose major challenges to global food security and rural livelihoods [3,4]. African dry forests, the largest vegetation formation are among those affected by climate change problems. Since, the majority (>70%) of the Ethiopian land masses are dry land, characterized by erratic rainfall, extreme drought, and flash floods, the impact seems particularly intense [1].

Farmers residing in many drought-prone regions seek to improve their life through growing of multipurpose trees that provide food, fodder, nutrients, timber, firewood, and mitigating the climate change impact [5,6]. *Tamarindus indica* L. (hereafter *T. indica)* is one of the multipurpose trees in sub-Saharan zones and traditionally builds resilience to the farming systems [7,8]. Beyond maintaining ecological sustainability [9,10], *T. indica* is an indigenous semi-evergreen tree species of the Fabaceae family, widely distributed across the sub- and semi-arid tropics [7,11] and is preferred for its wild edible fruit and timber [7], fodder for animals [12], medicinal value [13–18], food [18,19] and improve soil fertility [9,10].

In several parts of the tropics, *T. indica* is an agroforestry tree species due to its multiple uses [7,9,20,21]. However, current studies have remarked poor recruitment [22,23] and low densities. Similarly, this species is highly threatened and limited only in the river basin of Ethiopia, particularly in the study area. Moreover, *T. indica* is listed on the IUCN Red List of Threatened Species [24]. Many species are being threatened by climate change [3,25]. Scholars have confirmed that dry land forests and woodlands are under pressure risk of extinction and shifts to pole wards and/or a higher elevation [3,26,27]. For instance, *Balanites aegyptiaca* [28], *Adosania digitata* [29], *Hagenia abyssinica* [30], Ethiopian wolves [31], *Dracaena ombet* [32], Ethiopian endemic birds species [33] and *Juniperus procera* [34] are among those species that are to declining in their distribution or at risk of extinction from their natural habitats in Ethiopia. However, the distribution and fate of *T. indica* is not investigated, particularly in the study area. There is no evidence on how the distribution and what suitable habitat might happen to the species under different greenhouse gas emission baselines. There is no or little information available on how climatic conditions locally influence its ecological distribution, abundance and productivity in

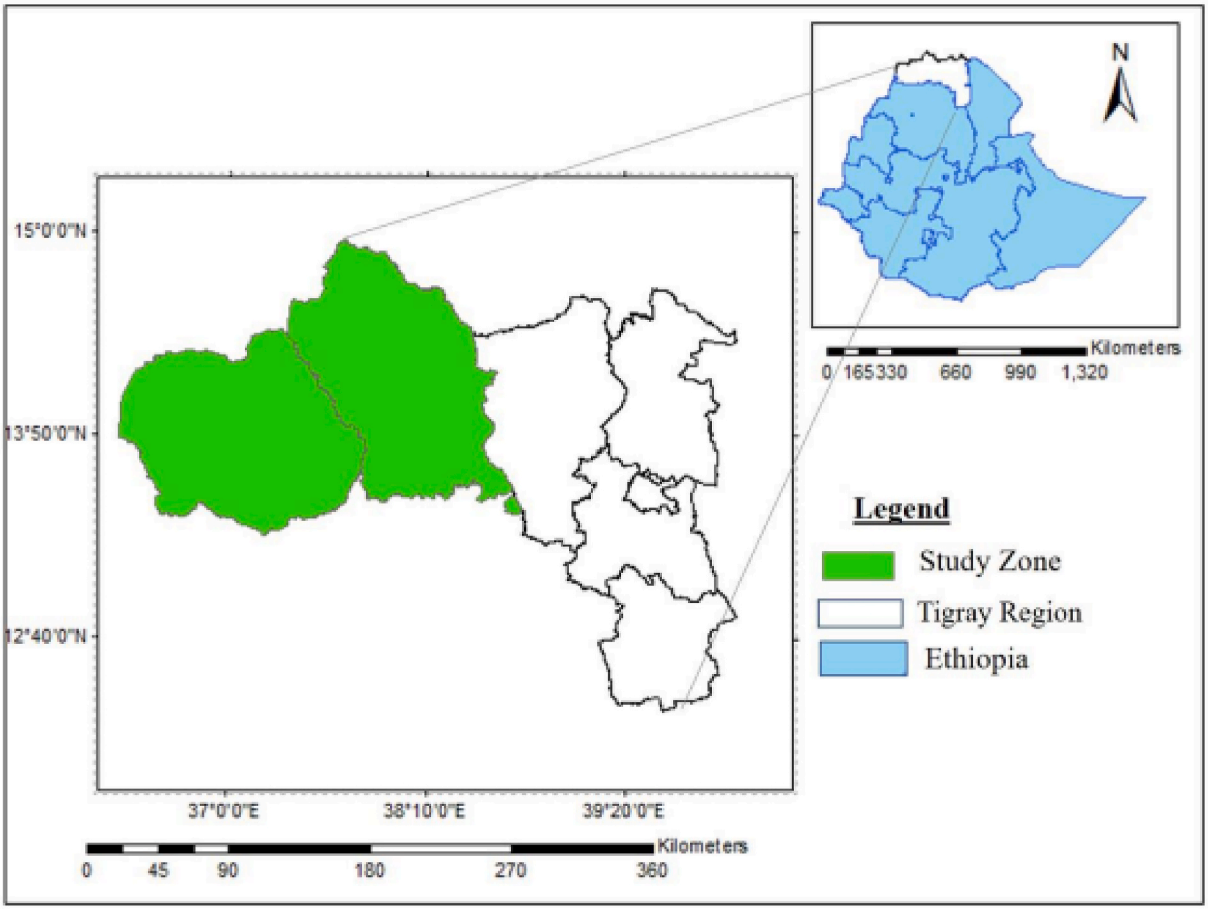

Fig. 1. Location map of the study region.

Africa [8,23], particularly in the study area. Previous studies have provided information on morphological and genetic diversity, potential productivity, and nutritional and medicinal properties [12,13,16,35]. Therefore, our aim is to fill the knowledge gaps about the species by investigating the impacts of climate change on its future distribution and abundance.

Species distribution models (SDMs) are ecological tools that help to predict species distribution by combining known occurrence records with digital layers of environmental data [36]. They can be used to assess climate change impacts and conservation management issues [37–39]. Currently, Maximum Entropy (MaxEnt) modeling approach is widely used in many studies to investigate climate change impacts on species distribution [7,29,34,38,40,41] and detect suitable areas for species conservation and to avoid extinction [41–45]. Compared to other SDMs such as GLM, Bioclim and GARP, MaxEnt has been shown to perform well [46]. Therefore, we used MaxEnt model to examine the distribution and future suitable habitat for the species. Thus, by assuming that climate change is one of the most important factors to determine the future distribution of species [3,47], we hypothesize that (1) The expected temperature elevations and precipitation variation are the major environmental factors to change *T. indica* distribution in Tigray, Ethiopia (2) *T. indica* distribution range much decreases in the climate change scenario of RCP8.5 than the 4.5 and (3) Future climate change shifts the altitudinal range of suitable habitats for *T. indica* in Tigray, Ethiopia.

2. Materials and methods

2.1. Description of the study area

The study was carried out in Tigray region, northern Ethiopia, (Fig. 1). Tigray is geographically located at 12°15'N to 14°57'N latitude and 36°27'E to 39°59'E longitude. It obtains an annual temperature ranging from 8.1^{0}c and 37^{0}c and annual rainfall ranging between 308 and 1054 mm [41]. It inhibits an altitude of 500–4000 m.a.s.l. The region covers 53,000 square kilometers (km^2) [41]. The dominant soil groups in the region are Leptosols, Vertisols, Fluvisols, Cambisols, Regosols, Luvisols, Arenosols, Calcisols, Xerosols, and Phaeozems [48–53].

2.2. Data collection and sampling procedures

In the north-western and western zones of the Tigray Region, 220 species locations points with a distance between points larger than or equal to 1 km were gathered. The data, in decimal degrees, were collected using Garmin 72H GPS from the identified *T. indica* occurrence sites. Besides, number of *T. indica* within a 50 m × 50 m (2500 m^2) plot in each selected plot (point locations) was collected. Apart from that, soil types/properties, slope and aspect were used as predictor variables to run the model [54]. The 19 bioclimatic data with a 1 km resolution and altitude (Supplementary information, Table 1) were downloaded from WorldClim-Global data. The soil data of Tigray were taken from the UNESCO soil map (http://www.fao.org/soils-portal/en/) while the slope and aspect were derived from the Digital Elevation Model (http://ned.usgs.gov). All the data were clipped down to the map of the study area using ArcGIS10.6. Baldwin [55] indicates that more than 30 presence points are sufficient to predict the existing and future potential distribution of a species. However, in order to increase the predicting power of the model, we intentionally increased the number of species occurrence points to 220 points.

2.3. Data analysis and modeling procedures

To estimate the impacts of reasonable future climate conditions on *T. indica* and considering the availability of the data, we used Representative Concentration Pathways (RCPs) under the General Circulation Model (GCM) called Climate Community System Model version four (CCSM4) from the Coupled Model Inter-comparison Project-phase 5 (CMIP5). The GCM was selected based on its consistent use across regions, particularly within sub-Saharan Africa [56,57]. In addition, as compared to the three GCMs (ACCESS1-0, CCSM4 & MIROC5) proposed for sub-Saharan Africa, CCSM4 was selected for the specific study areas [34,58].

The GCM was forced using two scenarios (RCP4.5 and RCP8.5) which are fed in three-time slices: current (i.e. 1950-2000), mid-of this century (2041–2060; average: 2050) and end-of the century (2061–2080; average: 2070) [54] to provide time-dependent projections of atmospheric greenhouse gas concentrations [59]. The medium and high greenhouse gas emission baselines (RCP45 and RCP8.5) were chosen because of the future increase in the emission of greenhouse gases as suggested by Beaumont et al. [60].

ArcGIS10.6 was used for analysis by coupling the environmental variables and the presence data of the species. Maximum entropy (MaxEnt) software version 3.3.3 k was used to model the present and future distribution of *T. indica* in the region because MaxEnt is well suited for species distribution modeling, has a high projecting performance and has the most accurate distribution function

Table 1
Habitat suitability threshold.

SN	Threshold value	Threshold description
01	0.652–1.0000	The geographical ranges of the excellent area
02	0.489–0.652	Optimum area
03	0.326–0.489	Suitable area
04	0.163–0.326	Less suitable area
05	0.0000–0.163	Unsuitable area

compared to other models [61–64]. Before running the model, we randomly divided the occurrence points into two parts; 75% to train the model and 25% to test the model. The software's settings were set to a maximum of 5000 iterations, 25% test percentage, and 10% training presence threshold. The remaining settings were taken as default. Making 5000 number of iterations allows the model to avoid over or under-predict [34,62,65]. As suggested for MaxEnt analysis, the environmental variables were converted to ASCII file format [66]. Finally, we run the SDM for 15 replicates and averaged the results to get superlative results [67].

Due to the absence of a universally valid single evaluation measure of model accuracy, we used both areas under the curve (AUC) of the receiver operating characteristic (ROC) and True skill statistics (TSS) to measure model performance. *AUC is* a single independent measure for model performance with values ranging from 0 (no better than random prediction) to 1 (*perfect prediction*) [62,68–71] *and is considered an effective measure for model performance. The TSS is a relatively new measure for the predictive performance of a model and has the advantage of correcting the overall model accuracy* [72]. *It is defined based on the components of* the confusion matrix *representing matches and mismatches between observations and predictions* [68,73]. Sensitivity and specificity are alternative techniques for model evaluation derived from the confusion matrix (Equation 1). Sensitivity measures omission errors as a percentage of predicted presences that are actually observed. Specificity measures commission error by the percentage of predicted observed absences [68,73]. Its value ranges from −1 to 1; where values from −1 to 0 indicate a performance no better than the random prediction, and a value of 1 indicate perfect prediction [68].

$$\text{TSS} = \text{Sensitivity} \ \backslash\ (\text{true presence}) + \text{Specificity}\ (\text{true absence}) - 1 \ldots \ldots \ldots \ldots \ldots \ldots \qquad \text{(Eq1)}$$

The models were accepted after it met the principle that the area under the curve (AUC) value became greater than 0.88 for test records [64] and the TSS values > 0.5 [68]. We also used Jackknife tests, percent contribution and response curves to identify the importance of each environmental variable for the model [66]. In order to avoid the likely errors, a 10% of minimum threshold was utilized to define the minimum probability of suitable habitat. The rest 90% of the data was applied to determine the suitable habitat. After the continuous values (0–1) obtained from MaxEnt, suitability habitats were identified based on the following threshold category (Table 1) [41,74].

The future impact of climate change on the suitable areas for the species was identified in DIVA-GIS 7.5 by overlaying and reclassifying the binary raster of current and future potential distributions and thus defined in four levels of suitability ranging from unsuitable (high-impact areas) to highly suitable (new suitable areas) [75] as (i) high-impact areas: areas where a species potentially occurs in the present climate conditions but will not be suitable in the future climate conditions (ii) areas outside the realized niche: geographic areas not suitable in both present and future climate conditions (iii) low-impact areas: geographic ranges where the species can possibly occur under both the existing and future climates; (iv) new suitable areas: areas which are not suitable for the occurrence of the species under current conditions, but will potentially occur in the future.

The altitudinal shift of the specie was determined by extracting elevation values for each point and calculating the area of occupancy of the species in the identified time slices [64,76,77]. The total area of the current and predicted habitat (suitable and unsuitable) was calculated using ArcGIS10.6 under the recognized RCPs and time slices. The relationship between the abundance of

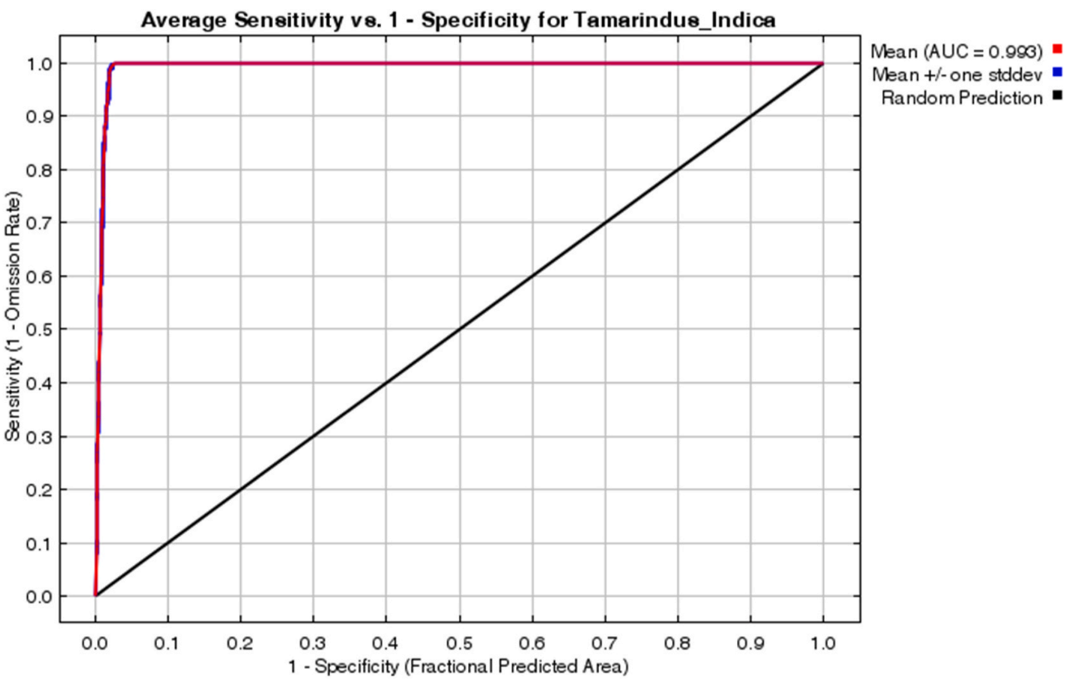

Fig. 2. The area under the curve (AUC) of the training and test data for the 15 replicate runs.

T. indica and environmental variables was conducted using multiple correlations using SPSS statistical analysis software (version 26). Before statistical analysis, the dependent variables (abundance of *T. indica*) were tested for normality using the Shapiro-Wilk test.

3. Results and discussions

3.1. Evaluation of model performance

The training and test area under curves (AUC) and TSS values for the 15 replicate runs were 0.993 (±0.001) and 0.7951 (±0.0428), respectively. In the AUC results (Fig. 2) the red (training) line depicts how well the model fits the training data whereas, the blue (testing) line indicates how well the model fits the testing data, and is the real test of the model's predictive power. Both the AUC and TSS results showed the MaxEnt-generated model of the training and test data fitted the model. Therefore, the Model is accepted as it fits the principles that AUC values greater than 0.88 [64] and TSS values greater than 0.5 [55,68,78] are the best performer model and have the ability to predict a higher probability of occurrence of the species. Other studies also showed that a model having AUC ≥90% is considered an excellent performing model [44,78–82]; therefore this MaxEnt-generated model fitted these principles.

The test line was very far from the random line and approached the top left of the graph; therefore, according to Phillips [83] and Phillips et al. [62] the model is better at predicting presence contained in the test sample of the data. Therefore for *T. indica,* we realized that the model has reached the level of excellent performance indicating that suitable conditions are predicted to be highly probable through most of the western and northwestern lowland areas of the Tigray region (Fig. 4).

3.2. Contribution of environmental variables to the distribution of T. indica

The MaxEnt selected the most important predictor bioclimatic factors from the WorldClim data-sets for the potential distribution of *T. indica* based on their order of contributions (Table 2) and jackknife test (Supplementary information, Fig. S1). Average values for the 15 replicate runs showed that the mean diurnal range (Bio 2) (56.9%) and temperature seasonality (standard deviation) (Bio4) (10.3%) had the highest percent contribution for the distribution of *T. indica* means MaxEnt used these variables more than other variables during modeling. In both the training gain and test gain of the jackknife outputs (Supplementary information, Fig. S1) the blue color bars indicated the contribution of each variable used for modeling the tree. Bio 2 was the most effective variable in both percent contribution and jackknife test outputs to predict the suitable habitat of *T. indica* in the region. The main environmental variables that determine the distribution of *T. indica* in their sequence of contributions (Table 2) were mean diurnal range (bio2), temperature seasonality (bio4), temperature annual range (bio7), precipitation seasonality (bio15), slope and precipitation of coldest quarter (bio19), which accounted for 88.7% of the modeling. Bio2 is the environmental variable that gave the highest gain when used alone. As such, it is considered to have the most useful information by itself. Therefore, bio2 is the best predictor single variable for the distribution of *T. indica.* The variable that reduces the gain in performance the most when removed was bio19, which therefore appears to contain the most useful information that other variables lack. Important variables showed high percent contribution and high decrease in gain when removed from the model. MaxEnt, therefore, answered which environmental variables matter most for the species being modeled. Once the MaxEnt model is trained, we can track which environmental variables contribute the most to the model [83]. High percent contributing variables help MaxEnt to fit to the training data [83].

3.3. Response of T. indica to the main contributing environmental variables

The response curves (Fig. 3) showed how each predictor variable affects the MaxEnt model projection. Each curve represents a unique model created by using the corresponding variable. The logistic output as indicated on the y-axis of each response curve is the anticipated suitable conditions for the species [83]. MaxEnt identified the mean diurnal temperature (bio2), temperature seasonality (bio4) and annual range in temperature (bo7) as the top three environmental variables that mattered most to the model performance. Areas that have optimum values of mean diurnal temperature of 16 °C–18.5 °C (Fig. 3a) and areas with temperature seasonality of 15 °C–26 °C (Fig. 3b) are suitable habitats for the distribution of *T. indica.* And areas which have temperature annual range of greater than 23 °C (Fig. 3c) are also suitable for the distribution of the species. However, when the temperature annual range exceeds 27.5 °C,

Table 2
Relative contributions of environmental variable to the MaxEnt model.

Variable	Percent contribution
bio2	56.9
bio4	10.3
bio7	9.2
bio15	5.6
slope	4.1
bio5	3.2
bio19	2.6
bio11	1.6
bio1	1.3

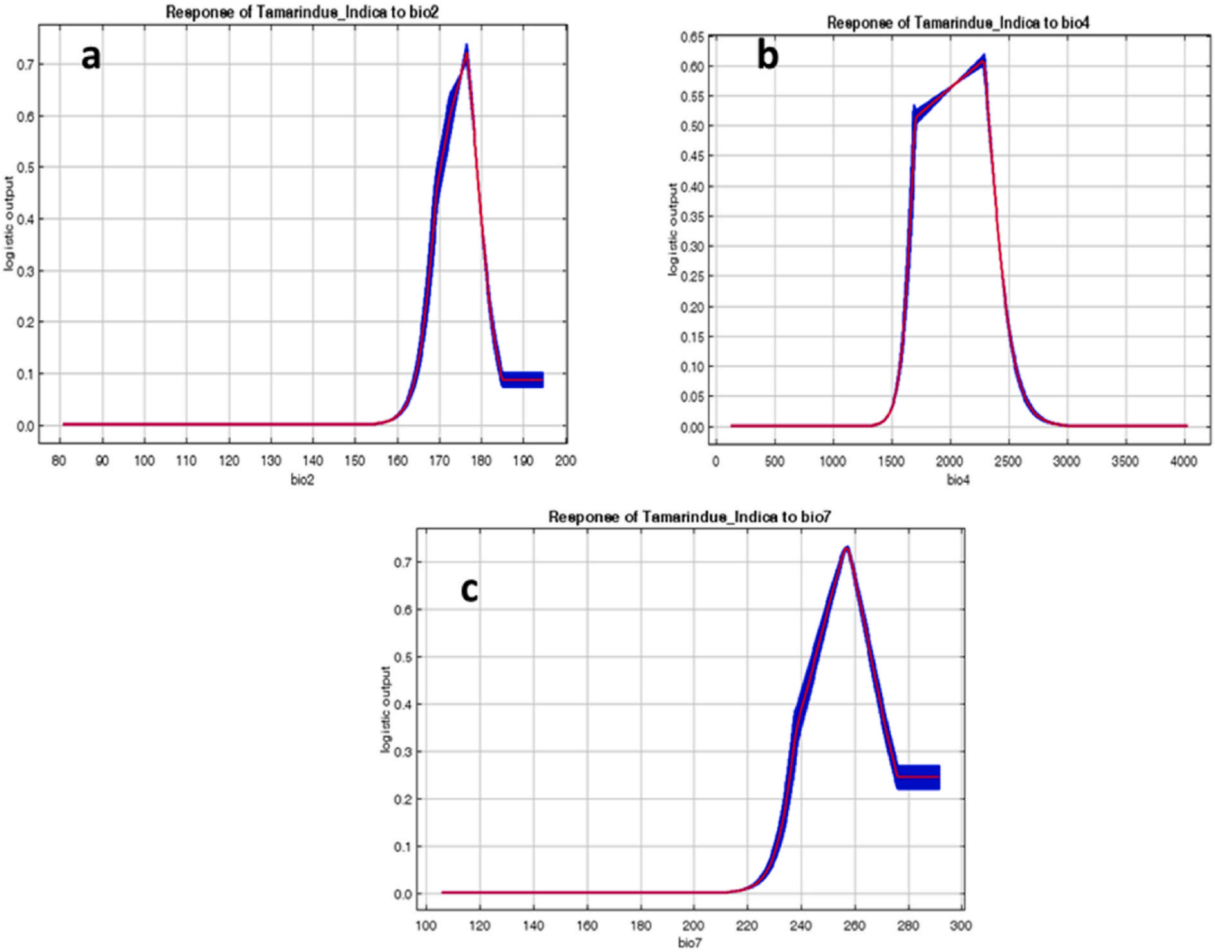

Fig. 3. Response curves of *T. indica* to the top three contributor variables. (a) Response of the species to bio2 (b) response of the species to bio4 and (c) response of the species to bio7.

the distribution of *T. indica* keeps constant.

A similar study on *T. indica* in Senegal have been reported that temperature seasonality (bio4) and annual range in temperature (bio7) are the top two (first and second) important environmental variables [7]; however, in our model, these two variables are the second and third important contributors to the model. The researcher also stated that the most important environmental variables to explain *T. indica* distribution in sequence are temperature seasonality (bio4), annual range in temperatures (bio7), maximum temperature of the warmest month (bio5), precipitation of the wettest month (bio13) and precipitation of the wettest quarter (bio16) which is slightly different from this study as mean diurnal temperature (bio2) is the most contributing variable in our model. Orwa et al. [84] and Rivers and Mark [24] also indicated *T. indica* prefers temperature-associated environmental conditions between 20 and 33 °C, mean annual rain fall 350–2700 mm) and low altitude (0–1500 m).

3.4. Potential distribution of T. indica under current and future climate conditions

The ecological niche modeling suggested that the current distribution of *T. indica* in the study area is 9209 km^2 (Table 3 and Fig. 4) which is 14.04% of the total area of the Tigray region. This would have increased to geographic range from 14.04% (current) to 11,073 km^2 (16.89%) and 10,629 km^2 (16.21%) by the year 2050 under RCP4.5 and RCP8.5 radiative forcing scenarios respectively. By the end of the twenty-first century (2060–2080), the total suitable habitat will be increased to 29,363 km^2 (44.78%) and 11,046 km^2 (16.85%) under RCP4.5 and RCP8.5 scenarios respectively. Similarly, the suitability maps (Fig. 4) also showed an increase in areas suitable for the distribution of this multipurpose tree species, especially in the medium emission scenario (RCP4.5). This means the MaxEnt model predicted that greater areas will be changed from unsuitable to suitable (new suitable areas) than suitable to unsuitable areas (high-impact areas) in 2070-RCP4.5. Our finding is also in line with the study of Bourou et al. [7] that indicated the suitable habitats for the distributions of *T. indica* in northern parts of Senegal were predicted to increase by 2050.

Studies indicate that the distribution and suitable habitat of the tree species is likely to decline under future climate scenarios [26, 85,86]. Unlike our assumption, this result showed that the potential distributions of *T. indica* in the study areas have a direct

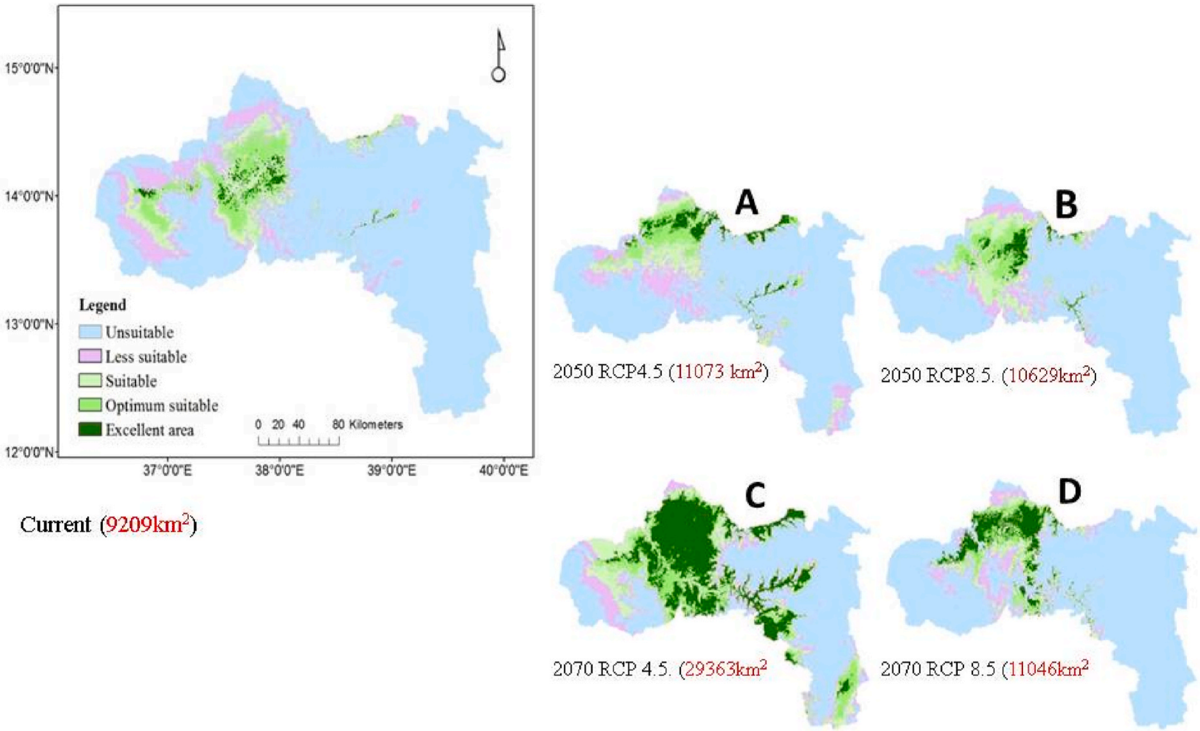

Fig. 4. Environmental suitability and future distribution maps of *T. indica* in Tigray, northern Ethiopia.

Table 3
The current and future distribution of *T. indica* in Tigray, northern Ethiopia.

Time slices	Distribution in Km^2	Percent
Current	9209	14.04
2050-RCP4.5	11,073	16.89
2050-RCP8.5	10,629	16.21
2070-RCP4.5	29,363	44.78
2070-RCP8.5	11,046	16.85

relationship with future climate change. Though *T. indica* is listed on the IUCN Red List of Threaten Species [24], our study revealed that climate change does not negatively affect the future distribution of *T. indica*. There will rather be newly suitable areas created in response to future climate changes. Climate change especially an increase in temperature is not a reason for the species to be under threat. The factors threatening the distribution of the species in Tigray region might be due to illegal cutting, fuelwood collection, agricultural expansion, lack of replanting, timber harvest, deforestation in general, flooding, lack of management, and soil erosion [18].

A study in Benin by Fandohan et al. [8] also reported the current geographical distribution and tree density of *T. indica* in the Sudano-Guinean region is limited and will be fading out from some locations of the region and the major threats mentioned were abundant tree felling for construction and agricultural expansions, and other human activities like debarking for medicine, pruning for fodder and fruit harvest.

The MaxEnt predicted the future new suitable areas and high-impact areas (Table 4). The future new suitable habitats of the species (areas not suitable at the current time but will be suitable for the future) under 2050-RCP4.5 and 2070-RCP4.5 scenarios will be 4829 km^2 and 25257 km^2 respectively. However, the high-impact areas (areas that will be changed to unsuitable) under 2050-RCP4.5 and

Table 4
Future climate change impacts on *T. indica* distribution.

Time slices	High impact areas	Areas outside of the realized niche	Low impact areas	New suitable areas
2050-RCP4.5	3348	56462	933	4829
2050-RCP8.5	2081	58883	2200	2408
2070-RCP4.5	176	36034	4105	25257
2070-RCP8.5	2807	55765	1474	5526

2070-RCP4.5 will be 3348 k m^2 and 176 km^2 respectively.

In the RCP8.5 scenario, the high-impact areas under 2050-RCP8.5 and 2070-RCP8.5 will be 2081 km^2, and 2807 km^2 respectively. The new suitable areas under 2050-RCP8.5 and 2070-RCP8.5 will be 2408 km^2 and 5526 km^2 respectively. Therefore, this result explained that areas that will be changed into suitable habitats in the future are greater than areas that will be changed into unsuitable habitats, especially under the 2070_RCP4.5 scenario.

3.5. Altitudinal shift of *T. indica* in response to the future climate changes

The current geographic range of the suitable habitats for *T. indica* in the region is between the altitude of 630–1564 m.a.s.l. (average = 1097 m.a.s.l.) (Table 5); this result is comparable with reports of Orwa et al. [84] and Rivers and Mark [24] which state *T. indica* grows well at a wide range of climatic conditions (mean annual temperature of 20–33 °C, mean annual rainfall 350–2700 mm) and in low altitude (0–1500 m.a.s.l). The current suitable geographic range of the suitable habitats for the species will shift to an altitudinal range of 674–1924 m.a.s.l (average: 1097 m.a.s.l) and 578–2367 m.a.s.l (average: 1473 m.a.s.l) in 2050-RCP4.5 and 2070-RCP4.5 climate scenarios respectively. While under the RCP8.5 scenario, the altitudinal range of the current suitable habitat will be shifted to a geographic range of 737–1550 m.a.s.l (average: 1144 m.a.s.l) and 778–1769 m.a.s.l (average1274 m.a.s.l) by the years 2050 and 2070 respectively. In both scenarios, the projected altitudinal range where *T. indica* survives will be wider than the current. And the average altitude where *T. indica* survives will be changed from 1097 m.a.s.l. (current) to 1473 m.a.s.l. and 1274 m.a.s.l. at the end of the century under RCP4.5 and RCP8.5 respectively.

In general, MaxEnt projected the probability of suitable habitats for *T. indica* to occur were in the lowland areas of the western, north-western and to some extent in the central parts of the Tigray region. Especially under the 2070-RCP4.5 scenario, the suitable habitat will become a wider range with the future rising temperature (Fig. 4). The limitations of this study in CMIP5 are primarily found in various climate scenarios and GCM outputs. This is because the RCP scenarios consider a large drop in atmospheric aerosol emissions as well as a wide range of model responses and climate sensitivities [87,88]. Hence, in the IPCC Sixth Assessment Report (AR6) the latest set of climate scenarios has been developed with many updated climate model outputs (CMIP6), based on the “Shared Socioeconomic Pathways” (SSPs) [89–94]. SSPs are considered more realistic future scenarios and make assumptions about how population, energy use, education and technology change over the next century, and combine them with the assumptions about the level of emission pathways [88,89]. Further, to incorporate the socio-economic development’s impact on the species distribution modeling using the recently introduced SSPs scenarios needs to be conducted.

3.6. Relationship between the abundance of *T. indica* and predictor variables

The relationships between the abundance of *T. indica* and the environmental variables were analyzed using Spearman’s multiple correlations because the dependent data were not fit a normal distribution. Results showed that the mean abundance of *T. indica* in the 50 m* 50 m plot was 3.02 ± 2.41 trees. The maximum number of trees found was 15 per plot; the minimum number was one tree per plot. The Spearman’s correlation result shows altitude, soil pH, temperature, percentage of silt (%silt) and rainfall have significant contributions to the abundance of the species while aspect, bulk density, cation exchange, percentage of sand (%sand) and soil organic carbon (SOC) content have not significant contribution (Table 6). Temperature, soil pH, percent of silt contents of soils and rainfall have a direct relationship. However, altitude has a negative correlation with the abundance of the species. This means as elevation increases the abundance of *T. indica* as well as the probability of finding suitable sites for the species decreases. This result is in line with reports by Orwa et al. [84] and Rivers and Mark [24] that stated *T. indica* grows well in low altitudinal range (0–1500 m.a.s.l) well-drained deep soils, warmer annual temperatures (20–33 °C) and a relatively higher annual rainfall (350–2700 mm).

4. Conclusions

This study investigated the top environmental variables that contribute most to the distribution of *T. indica* are mean diurnal range (bio2), temperature seasonality (bio4), temperature annual range (bio7), precipitation seasonality (bio15), slope and precipitation of coldest quarter (bio19) and these accounted for 88.7% of the modeling.

The geographical range of *T. indica*, which is currently 9209 km^2, would have increased to 29,363 km^2 (44.78%) by 2070 under the RCP4.5 scenario. In contrast, the size of the suitable habitats will expand to 11,046 km^2 (16.85%) by 2070 under the RCP8.5 scenario. Particularly in the context of the 2070-RCP4.5 scenario, the western and north-western lowlands as well as to some extent in the

Table 5
Altitudinal shift of *T. indica* in response to climate changes in 2050 and 2070.

Scenarios	Altitude range (average) m.a.s.l
Current	630-1564 (1097)
2050-RCP 4.5	674-1928 (1301)
2050-RCP 8.5	737-1550 (1144)
2070-RCP 4.5	578-2367 (1473)
2070-RCP 8.5	778-1769 (1274)

Table 6
Correlations between abundance of *T. indica* and Environmental variables.

	altitude	aspect	Bulk density	Cation	clay	ph	rain	%sand	%silt	SOC	Mean temp
Abundance	−.268**	−.029	.053	.115	.009	.185**	0.183**	.082	.142*	.089	.225**
Sign.	.000	.676	.438	.095	.900	.007	.008	.233	.039	.197	.001

**Correlation is significant at the 0.01 level (2-tailed); *. Correlation is significant at the 0.05 level (2-tailed).

central parts of the region are identified as suitable habitats for *T. indica* to exist.

Altitude, soil pH, temperature, percentage of silt (%_silt), and rainfall have significant positive contributions to the abundance of the tree. However, altitude shows a negative correlation with the abundance of the species. This means as elevation increases the probability of finding suitable sites for *T. indica* decreases. Therefore, in the two scenarios (RCP4.5 and RCP8.5), the future climate impact on the geographic distribution of *T. indica* is expected to be positive. However, it should be noted that the main reasons for the decline of the species as mentioned in other literatures might be attributed to human influence. Though the species is currently under threat and listed on the IUCN Red List of Threaten Species, the MaxEnt model predicts that suitable areas will become wider with future climate change. Therefore, conducting larger-scale studies worldwide, investigating the main reasons for the decline of suitable habitats for the species, integrating river networks with bioclimatic predictor variables and implementing conservation programs are recommended.

Author contribution statement

Yirga Gufi: Performed the experiments; Wrote the paper.
Ashenafi Manaye: Conceived and designed the experiments; Wrote the paper.
Berihu Tesfamariam: Conceived and designed the experiments; Wrote the paper.
Haftu Abrha: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.
Musse Tesfaye: Conceived and designed the experiments; Wrote the paper.
Sibhatleab Hintsa: Analyzed and interpreted the data.

Data availability statement

Data will be made available on request.

Additional information

Supplementary content related to this article has been published online at [URL].

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e17471.

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