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Research article

Species distribution modelling of *Monotheca buxifolia* (Falc.) A. DC.: Present distribution and impacts of potential climate change☆

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A B S T R A C T

Species distribution modelling (SDM) is an important tool to examine the possible change in the population range and/or niche-shift under current environment and predicted climate change. *Monotheca buxifolia* is an economically and ecologically important tree species inhabiting Pakistan and Afghanistan in dense patches, and species range is contracting rapidly. This study hypothesize that predicted climate change might remarkably influence the existing distribution pattern of *M. buxifolia* in the study area. A total of 75 occurrence locations were identified comprising *M. buxifolia* as a dominant tree species. The Maximum Entropy (MaxEnt) algorithm was utilized to perform the SDM under current (the 1970s–2000s) and two future climate change scenarios (shared socioeconomic pathways: SSPs 245 and 585) of two time periods (the 2050s and 2070s). The optimal model settings were assessed, and simulation precision was assessed by examining the partial area under the receiver operating characteristic curve (pAUC-ROC). The results showed that out of 39 considered bio-climatic, topographic, edaphic, and remote sensing variables which were utilized in the preliminary model, 6 variables including precipitation of warmest quarter, topographic diversity, global human modification of terrestrial land, normalized difference vegetation index, isothermality, and elevation (in order) were the most influential drivers, and utilized in all reduced SDMs. A high predictive performance (pAUC-ROC; >0.9) of all the considered SDMs was recorded. A total of about 67,684 km^2 of geographical area was predicted as suitable habitat ($p > 0.8$) for *M. buxifolia*, and Pakistan is the leading country (with about 54,975 km^2 of suitable land area) under the current climate scenario. Overall, the existing distribution of the tree species in the study area might face considerable loss (i.e. rate of change %; −27 to −107) in future, and simultaneously a northward (high elevation) niche shift is predicted for all the considered future climate change scenarios. Hence, development and implementation of a coordinated conservation program is required on priority basis to save the tree species in its native geographic range.

☆ The authors declare no competing interests.

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1. Introduction

Climatic, topographic, edaphic, and anthropogenic factors influence the geographical distribution pattern of the plant species, and vegetation structure and composition [1]. A continuous increase in global temperatures is reported by Inter-governmental Panel on Climate Change since the very beginning of the 20th century. The average land surface temperature (LST) has climbed by 0.85 °C worldwide, especially from the late 1800s–2012s, and amount of greenhouse gas emission has also been dramatically increased [2]. The relative concentration of CO_2, CH_4, and N_2O gases in the atmosphere has also reached to their highest over the last 800,000 years [3]. Human-induced climate change is becoming more evident in the form of increasing anomalies in both temperatures and precipitation. These variations are inducing a greening trend in some mountainous areas of the sub-continent due to high precipitation at one end [4,5], while drought and water shortage at the other parts of the world on the other hand. Abnormal environmental variations mainly climatic and anthropogenic ones disrupt multiple ecosystem functions including plant recruitment, phenology, soil properties, and assist in spreading plant diseases, and pest and parasite invasions etc [6].

In species distribution modelling (SDM), different environmental limitations of a species are evaluated in space and time by adopting either single or multiple statistical algorithms simultaneously [7,8]. The commonly used tools include generalized linear and additive models (GLMs and GAMs), and machine learning techniques (e.g. maximum entropy (MaxEnt), random forest (RF), boosted regression tree (BRT) and artificial neural networks (ANNs), etc.) [9]. Among these, MaxEnt tool is the most popular one, and works on the postulate of maximum entropy i.e. “how much choice is involved in the selection of an event” [10]. MaxEnt requires species presence data only, and also works efficiently even with the low number of species presence records, and has a user-friendly interface [5]. Another advantage of MaxEnt algorithm includes the restriction of the value of each environmental variable to its factual average [11,12]. The number and types of environmental variables, sampling effort, sampling bias, and amount and extent of species occurrence data affect prediction probabilities [11], and MaxEnt relatively can handle these issues more adequately than the other modelling tools. Species distribution models (SDMs) can predict high occurrence probability for individual species at some geographic space/places [7,13], which depict an existence of more optimal environmental conditions, and can be called as a suitable habitat [14].

The species niche concept provides a basis for the development of BIOCLIM (the first SDM package) [15,16]. The WorldClim databases have provided an important source of global climatic data for SDM studies [17,18]. The WorldClim data were developed using ANUSPLIN, a climatic interpolation method, developed initially for BIOCLIM and a set of 19 bioclimatic variables prepared in 1996 for a revised version of BIOCLIM [19]. Predictive distribution modelling of different valuable plant species has been conducted by many workers to forecast the impact of expected climate change on biodiversity [20–22]. Such studies are valuable for the timely development and execution of conservation planning and management. Additionally, species response in the form of growth and survival can be assessed under predicted future climate change scenarios like SSPs 126, 245, 370 and 585 for multiple time periods including say 2030s (2020s–2040s), 2050s (2040s–2060s), 2070s (2060s–2080s) and 2090s (2080s–2100s), etc. This data comes under the sixth phase of the Coupled Model Intercomparison Project (CMIP6) based on global anticipated greenhouse gas emission and socio-economic development scenarios.

M. buxifolia (Falc.) A. DC., locally known as “Gurguri” is one of the important broadleaved tree species of the family Sapotaceae. It is a native of the remnant forests and is narrowly distributed predominantly along the border areas of both Pakistan and Afghanistan [23,24]. The fruit of this species is laxative, digestive, and commonly found effective against the urinary tract diseases. Despite the presence of many valuable plant species, *M. buxifolia* is the most chosen one in the north-western parts of Pakistan. This is probably due to its high socio-economic value in the prevailing culture [25]. This tree species is used as fuel-wood, timber-wood, highly palatable by the camels and goats, and also used in fencing and as a windbreaker around the fruit gardens and cultivated cropland [3]. *M. buxifolia* is economically valuable for local inhabitants of rough and tough mountainous areas. The communities residing in remote mountainous areas usually have poor conventional horticultural and agronomic activities. Therefore, due to multi-purpose usage, this tree species is facing severe anthropogenic pressure which resulted in reduction of its distributional range and population size dramatically during the last few decades [4]. These ever-increasing anthropogenic activities and predicted climate change might be leading threats to this species in near future in the area [3].

Keeping this into consideration, this study was designed to explore and predict the potential habitat suitability and distribution pattern of *M. buxifolia* using SDM tools under varying climatic conditions. The main objectives of this study include to answer the following un-explored questions, 1) which environmental variables predominantly influence the *M. buxifolia* distribution? 2) Identification of core geographical areas that are ecologically and environmentally suitable for this tree species under current and predicted future climate change scenarios? 3) Will the ecological niche of the species dwindle and/or shift under the predicted future climate? The findings of this study will not only help in identification and mapping of core geographical areas with high habitat suitability for the considered species but might also help in delimiting the potential conservatory areas, and in maintaining the sustainable growth of the dependent local communities.

2. Material and methods

2.1. Study area

Pakistan and Afghanistan are the two neighboring countries whose geographic space (especially border areas) have optimal environmental conditions necessary for the growth and survival of *M. buxifolia*. Ecologically, this tree species is a niche specialist and distributed in dense patches but at spatially distinct locations having unique environmental conditions. This tree species is frequently reported from different geographic areas including the Hindukush Mountains especially the bordering areas of both countries, and western Himalaya [25]. Pakistan has a land area of about 882,364 km^2, spanning between 60°55′–75°30′ E longitude and 23°45′–36°50′ N latitude [26]. The country has immense variety in its climate, topography (elevation gradient ranging from 0 to 8611 m asl) and biodiversity [23,27]. As far as Afghanistan is concerned, the species is primarily distributed in the eastern parts adjoining north-western Pakistan, and the area on both sides have strikingly similar climatic conditions. Due to continuous geopolitical conflicts in Afghanistan, this study collected the species occurrence data from Pakistan only but extensively covered the border areas. Hence, the existing core areas of the considered species are thoroughly surveyed to get location data, and SDM was performed by selecting an extent of X-Min: 68, X-Max: 77, Y-Min: 29, Y-Max: 37 to clip the environmental variables for both current climate and future projections. The forests of this species are found on moderate to steep slopes with ecologically unique microhabitats [3]. These mixed forests are comprised of patches of evergreen, deciduous, and broad-leaved trees and shrub species. Hence, occasionally, these forests develop into a dense ground cover of steppe vegetation in the area. The various landscapes serving as the preferred ecologically suitable habitat for *M. buxifolia* are presented in Fig. 1.

2.2. Species occurrence data

Preliminary field and botanical literature surveys were conducted in 2016 to get familiarity with *M. buxifolia* habitat and distribution range. Local knowledgeable community members and forest offices were also contacted to get help in search of *M. buxifolia* locations. Finally, a total of 75 sites were recognized fulfilling the following two conditions; a) species should be uniformly distributed over an area of more than 1 ha, and b) study locations should be dominated by the *M. buxifolia* in terms of its relative abundance comparative to coexisting species [28]. The geographical coordinates of the diagonal intersection point (1-ha plot) at each site were collected by a handheld GPS device from March 2017 to August 2019. These coordinates were used as presence locations to build the SDM. Different taxonomic databases like POWO (URL: https://powo.science.kew.org/taxon/urn:lsid:ipni.org:names:915493-1; accessed: 25-11-2022) suggests that *M. buxifolia* is a synonym of *Sideroxylon mascatense* (A.DC.) T.D.Penn. Though, this tree species is also reported from some parts of Africa (Somalia, Ethiopia) and Arabian Gulf countries (Kingdom of Saudi Arabia, Qatar and Yemen), however, primarily detected as a highly scattered tree species (low relative density) in these arid areas, and do not meet the set two conditions of this study as mentioned above. Therefore, this study includes 75 occurrence locations of the target tree species representing the core areas of the species. A buffer analysis was also performed, and a circular buffer zone with 1 km^2 radius (as environmental data used in this study has a spatial resolution of about 1 km^2) was created around each species presence point to confirm spatial and environmental distinctiveness (i.e. to maintain the minimum ground distance of 2 km^2 between any two closely located presence points, and to delimit one presence point in any pixel). The modeled predictions were mapped by using ArcGIS (ver. 10.3), whereas SDM was done by using open source MaxEnt (ver. 3.4.4) software (Source: https://biodiversityinformatics.amnh.org/open_source/maxent/).

Fig. 1. A collection of few images representing distribution of *Monotheca buxifolia* forests at the different study locations in the Hindu Kush mountain range, Pakistan.

2.3. Environmental data collection

As plant species distribution is influenced by a variety of environmental factors say climatic, topographic, edaphic and anthropogenic, hence, predictor variables data was selected accordingly. A total of thirty-nine predictor variables were used in preliminary distribution model of *M. buxifolia* to seek their influence and contribution (%). These include 19 bioclimatic variables Product: Coupled Model Inter-comparison Project Phase 6 (CMIP6); File format: Geo-Tiff (.tif); Resolution: 30 arc-seconds (ca: 1 km^2) available at WorldClim database (URL: https://www.worldclim.org/data/worldclim21.html) [18], 10 different edaphic variables (mean values of 0–30 cm soil depth; *Source:* https://soilgrids.org/), 7 topographic variables (Google Earth Engine Data Catalog), 2 anthropogenic variables including population density and global human modification of terrestrial land (Source: Google Earth Engine Data Catalog contributed by Conservation Science Partners), and NDVI (mean value (2001–2020) of the growing season (April–August)), the detail of the predictor data is presented in Table S1. The global human modification of terrestrial systems data set depicts human modification of the terrestrial lands, and comprise of continuous 0–1 metric raster data. It reflects the proportion of a landscape as a human-induced modified region considering the physical extents of 13 important anthropogenic stressors/factors say population density, built up areas, cropland, livestock, major and minor roads, tracks, railroads, mining, industries, oil wells, wind turbines, power lines and night time lightings (source years: 2000–2016) [29]. The predictors' data is resampled to bioclimatic variables resolution (~1 km^2), if required, before running SDMs to match the pixel size of each variable. The future projection data (i.e. two predicted future climate change scenarios including SSPs 245 and 585 of time periods the 2040s–2060s = the 2050s and the 2060s–2080s = the 2070s) with 30 s resolution was obtained (*Source:* https://www.worldclim.org/data/cmip6/cmip6_clim30s.html) [22]. This future data belongs to three global climate models (GCMs) including 1. BCC-CSM2-MR; 2. CanESM5; 3. CMCC-ESM2, and the mean valued future prediction raster files were created and compared to seek the possible impact of predicted future climatic variations.

2.4. Predictor data filtration and variables selection

In the first step of SDM of the tree species, a preliminary MaxEnt model was run with default settings using all the considered variables to obtain the variables' importance. A threshold value of >1% contribution was used to screen the variables. The variables with more contribution than the selected threshold value were used to evaluate for their pairwise correlation analysis (threshold value of ±0.7 for the Pearson's correlation coefficient) in the second step. Any two variables if found correlated above threshold, the one least contributing was removed. This two-step procedure help to reduce the multicollinearity effects of the covariates in the final reduced models [26], as use of environmental variables giving redundant information (highly correlated) results in model over-fitting. This sequential procedure help in selecting the highly contributing but least correlated predictor variables for the final reduced-uncorrelated model. Accordingly, implementing the two thresholds mentioned above, six variables including precipitation of warmest quarter (Bio18), topographic diversity, global human modification of terrestrial land, normalized difference vegetation index, isothermality (Bio3), and elevation were retained. Pairwise correlation plots of the final selected variables for the reduced models were developed (Fig. S1) by using "ggplot2" and "reshape2" packages in R statistical software.

2.5. Model calibration and optimization

The SDMs calibration and optimization is an important step in predictive distribution modelling for better and more reliable prediction probabilities [22]. For optimal SDMs, multiple varying combinations of feature classes (FC: L = Linear; Q = Quadratic; P = Product; H = Hinge; and T = Threshold), and regularization multiplier (RM) values can be assessed [30]. For this, "ENMeval", "rJava", "raster", "mass", "dismo", and "rgdal" packages in R statistical software were utilized. This study targeted a total of 48 different models with varied combinations of FC and RM values (six FC groups including L, LQ, H, LQH, LQHP, and LQHPT; and eight RM values: 0.5–4, interval: 0.5). The other selected options in this testing include10 k-fold cross-validation with 10,000 background points. Therefore, the optimal MaxEnt model settings were identified based on threshold-dependent (i.e., omission rate) evaluation metrics. Additionally, a two-dimensional kernel density estimation was made to generate the bias file to be used in all SDMs.

After identifying the appropriate and optimal MaxEnt settings, the other model run options include selection of complementary log-log (clog-log), response curves of the predictor variables, Jackknife testing to seek the importance of the explanatory variables, random seed, multivariate environmental similarity surfaces (MESS) analysis when projecting, 10 replicate runs, 10 percentile training presence threshold, and 500 random iterations (i.e. use of different set of occurrence locations for training and testing on each iteration). Similarly, MaxEnt analyzes the environmental conditions of the randomly distributed background points (10,000 point in current study), and compare them with the conditions of species presence records for determining the differences in habitat suitability (presence probability) of the species [31]. All the remaining options in MaxEnt were retained by default in the model.

2.6. Model validation and prediction probability classification

The SDMs performance can be independently evaluated by assessing the values of different accuracy measures like area under receiver operating characteristics curve (AUC-ROC), true skill statistics (TSS), Kappa statistics, AUC-ratios, and partial AUC-ROC values [18,20]. Multiple pros and cons (especially dependence on prevalence) of the first three accuracy measures have been reported from time to time [32]. Hence, this study calculated all the five accuracy measures mentioned above for comparative assessment of the SDMs. The pAUC-ROC values were calculated by using 95% confidence intervals. The values of AUC-ROC, pAUC-ROC and Kappa statistics varies from 0 to 1, TSS from −1 to +1, and AUC ratios from 0 to 2. The higher values (>0.9 or more close to

1 in case of first four measures and >1.8 or more close to 2 in case of AUC ratios) represent excellent model performance [33]. This mean that larger the partial areas under ROC curve, the better would be model performance [34,35]. Model accuracy values can be visualized in the form of graphs by plotting sensitivity verses specificity at different prediction probability threshold values. The curve values permit the comparison among the multiple models to seek their relative prediction performance [11]. All the model accuracy values were computed by using "spm", "SDMTune", and "pROC", packages in R statistical software.

The averaged prediction output of the 10 replicates runs with values varying from 0 to 1 were classified into five equal-sized categories as suggested many workers [22,32]. These include HSC-5 (Very high habitat suitability class: $p > 0.8$), HSC-4 (high habitat suitability class: $p > 0.6–\leq 0.8$), HSC-3 (moderate habitat suitability class: $p > 0.4–\leq 0.6$), HSC-2 (least habitat suitability class: $p > 0.2–\leq 0.4$), and HSC-1 (no habitat suitability class: $p < 0.2$). The use of such equal-sized prediction probability classes is relatively more intuitive, especially when comparing future prediction maps showing pairwise HSCs inter-conversions [36]. Univariate analysis of variance (ANOVA) and Tukey's post-hoc test was performed to seek the significant difference among the five groups (current and four future climate change options). The detailed methodology utilized in this study is presented in the flow diagram (Fig. 2). The total area (km^2) under each classified category was calculated by using map algebra in ArcGIS ver 10.3. The rate of change of each classified category (HSC-1–HSC-5) were computed to compare future prediction probabilities with respect to current probability values. Similarly, all the 75 studied locations were used to develop the extent of occurrence of the tree species using alpha hull method, and the "ConR" package in R statistical software.

3. Results

3.1. Model performance and variables significance

The maximum entropy algorithm was employed to anticipate the potential niche range and distribution pattern of economically important broadleaved *M. buxifolia* under current (1970s–2000s), and projected future (2050s and 2070s) climate change scenarios (SSPs 245 and 585). Ecological niche modelling (ENM) evaluation for the optimal model results suggested that a combination of LQH features coupled with RM value of 1.5 was the most appropriate for better SDMs performance. The predicted area and average omission rate of *M. buxifolia* showed that the model performed significantly better than the random when tested for omission. The results also depicted that the mean omission rate on the test data was best matched to the predicted omission rate along varying cumulative threshold values. Similarly, pAUC-ROC value for the test data represents "fit of the model", and predictive reliability. This study recorded the pAUC-ROC value of 0.978 or 97.8% (Fig. S2) for the test data under the current climate, and revealed an excellent model fit, optimal performance, and reliability. Similarly, pAUC-ROC values of >0.9 or 90% were recorded for all the future climate change scenarios considered in this study. Other accuracy measures targeted in this study like AUC-ROC, TSS and Kappa even responded better than pAUC-ROC values for each considered prediction model (Table S2).

The Jackknife testing shows the importance of explanatory variables in the prediction models. The order of importance of the six predictor variables in regularized training gain under the current climate scenario is presented in Fig. 3. The results showed that each selected explanatory variable contributed to the improvement of the model prediction. The reason might be the removal of highly collinear and least influential variables, and optimal model settings. The order of importance (with only variable) results depicted that Isothermality (Bio3) is the leading variable followed by precipitation of the warmest quarter (Bio18), global human modification of terrestrial land, elevation, NDVI, and topographic diversity. As far as the maximum training gain is concerned (without variable), precipitation of the warmest quarter (Bio18), topographic diversity, and NDVI were recorded as the most important variables. This means that there would be a maximum decrease in the training gain in case of removing Bio18 from the model (Fig. 3).

Percent contribution and permutational importance of the environmental variables are presented in Table 1. Based on percent contribution of the variables (in order) include precipitation of warmest quarter (Bio18: 30.3%), topographic diversity (Tdiv: 24.6%),

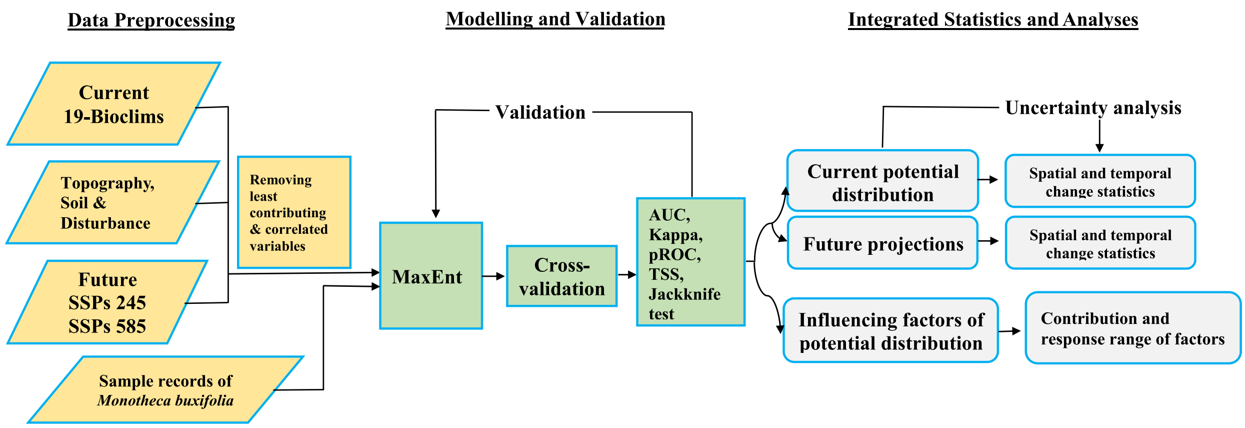

Fig. 2. Flow-chart depicting methodology employed in SDM of *Monotheca buxifolia* in the study area.

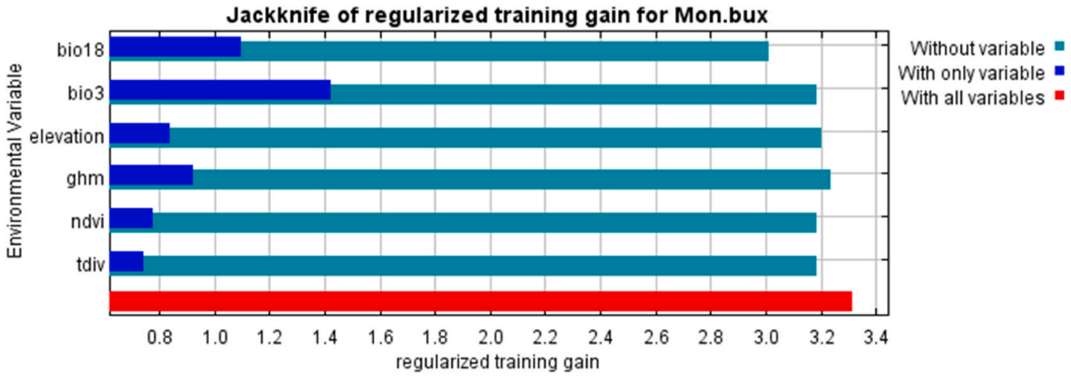

Fig. 3. Jackknife test of regularized training gain of the six most influential environmental variables and their importance detected in current climate (1970s–2000s) predictive model of *M. buxifolia* in the study area.

Table 1
Contribution (in percent) and permutation importance of the six bioclimatic variables in the predicted potential distribution pattern of *M. buxifolia* in the study area.

Code	Variable	Percent contribution	Permutation importance
Bio18	Precipitation of Warmest Quarter	30.3	28.9
Tdiv	Topographic diversity	24.6	16.3
gHM	Global Humana Modification dataset (CSP gHM)	23.2	4.2
NDVI	Normalized Difference Vegetation Index × 10,000	9.2	3.3
Bio3	Isothermality (BIO2/BIO7) (× 100)	7.6	9.3
Elevation	Elevation	5.1	38.1

global human modification of terrestrial land (gHM: 23.2%), NDVI (9.2%), isothermality (Bio3: 7.6%) and elevation (5.1%). Similarly, permutation-based order of importance was led by elevation (38.1%) followed by precipitation of warmest quarter (Bio18: 28.9%), topographic diversity (16.3%), isothermality (Bio3: 9.3%), global human modification of terrestrial land (gHM: 4.2%) and NDVI (3.3%).

3.2. Variables response curves

The MaxEnt model response curves are developed by using the corresponding variable values only, and presented in Fig. 4. In these response curves, x axis is represented by the variable value, and y axis by the predicted probability of the modeled tree species. The results depicted that optimal environmental conditions for the highest predicted probability of *M. buxifolia* occurrence include the geographic areas having isothermality (Bio3) range of 35–39%, precipitation of warmest quarter (Bio18) as 100–300 mm, elevation as 500–1500 m above sea level, moderate level of gHM as 0.4–0.6, NDVI (× 10,000) as (3000¬4500), and high topographic diversity index range as 0.6–0.9.

3.3. Distribution pattern under current climate

The MaxEnt predicted probability output was classified into five categories, mapped, and analyzed for land area calculation. Under the current climate scenario (1970s–2000s), a total of about 67,684 km^2 geographic area is predicted as suitable (having required environmental conditions for *Monotheca* tree species) in three neighboring countries including Pakistan, Afghanistan and India. The extent of occurrence (EOO) of the species was recorded as about 60,632 km^2 which is quite close to the total suitable geographic area for the species in the study area as mentioned above. However, this difference of about 7000 km^2 might be due non-availability and inclusion of species occurrence data from Afghanistan. Additionally, the majority of this 7000 km^2 of the geographic area came under least to moderate suitability (low predicted probability) classes. This also represents that historically the species might exist at these locations in the past (Fig. 5). Accordingly, out of the total suitable land area, about 7326 km^2 was predicted under very high suitability class (HSC-5), about 11,835 km^2 under high suitability class (HSC-4), about 16,575 km^2 under moderate suitability class (HSC-3), and about 31,949 km^2 under least suitability class (HSC-2) (Table 2). Based on countries, Pakistan is detected as the most suitable one having the majority of geographic areas with optimal environmental conditions required for the growth and survival of the considered tree species. About 7041 km^2 of the land area of Pakistan (out of a total of 7326 km^2 under HSC-5) is detected under HSC-5 (Table 2). Accordingly, Afghanistan has about a land area of 253 km^2, and Jammu and Kashmir, India has about 32 km^2 under HSC-5. Similarly, the land area under other habitat suitability classes say HSC-2 to HSC-4, and their patterns for these three countries are predicted like HSC-5 under the current climate scenario.

As far as the predicted microhabitats are concerned, Pakistan is detected as the leading host with multiple locations having optimal

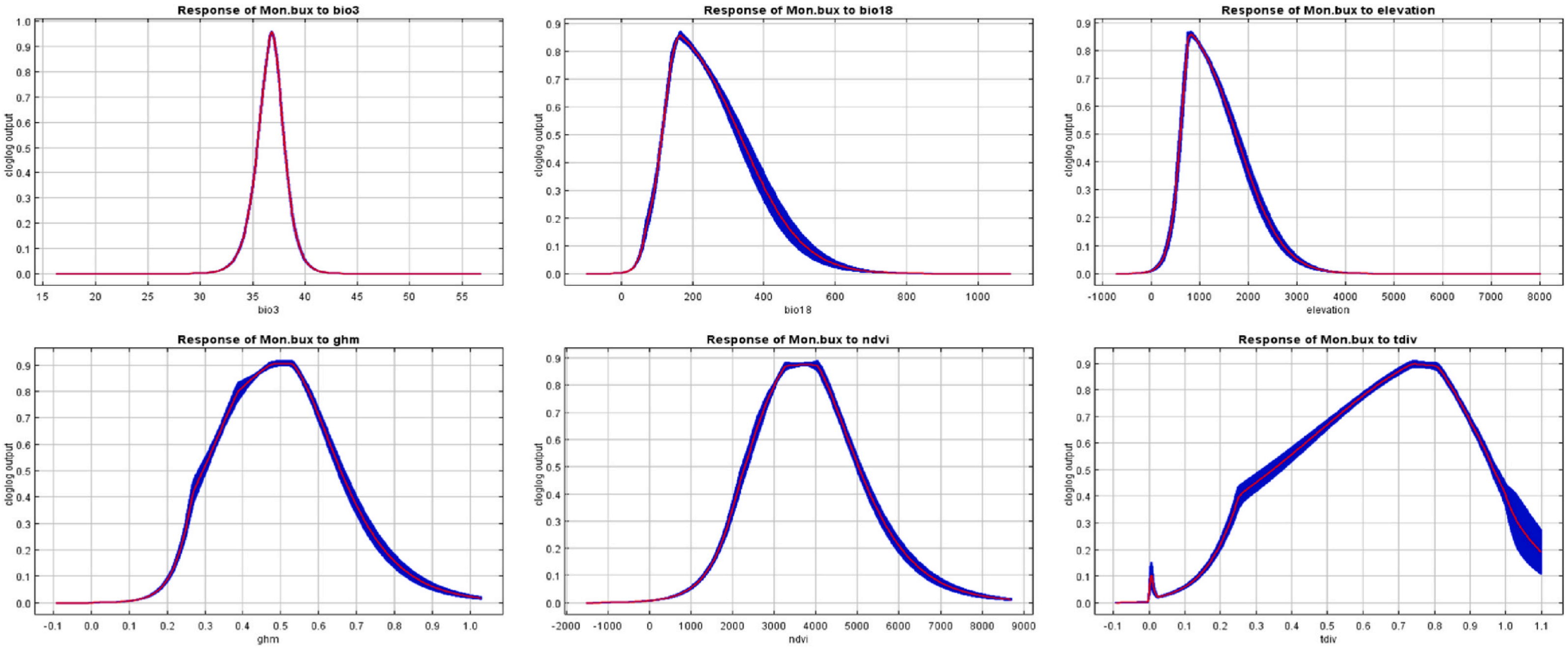

Fig. 4. MaxEnt model response curves of the six bioclimatic variables used in the species distribution modelling of *M. buxifolia*.

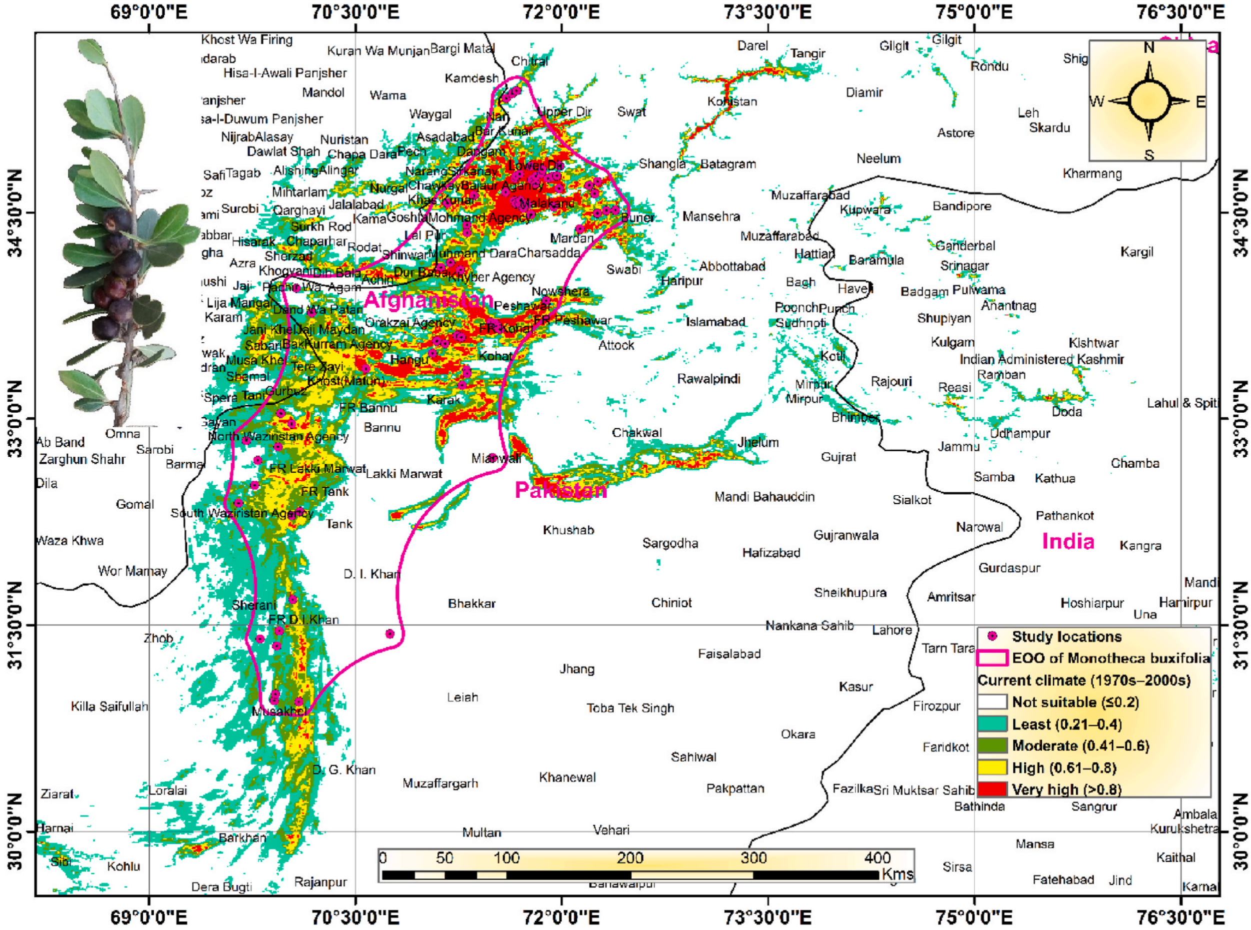

Fig. 5. Map displaying ecological niche variations of *M. buxifolia* under current climate (1970s–2000s) scenario in the study area.

environment for the *Monotheca*, and these include northwestern districts (allied to Pakistan-Afghanistan international border called Durand line) Bajaur, Malakand, Mohmand, Orakzai, Waziristan, Chitral, and Khyber, etc. The other important districts include Lower and Upper Dir, Swat, Karak, Hangu, Kohat, Buner Kohistan, Mianwali and salt range area in the Pothohar plateau. Afghanistan districts that have optimal environmental conditions include Achin, Sherzad, Jani Khel, Sabari, and Musa Khel whereas small land areas of Kupwara, Rajouri, Reasi, Srinagar, and Doda districts of Jammu and Kashmir, India. Hence, these microhabitats (locations) are represented by unique optimal environmental conditions and resulting rich biodiversity, and suitable for the modeled tree species.

3.4. Future prediction and distribution

A total of four SDMs based on two projected future climate change scenarios (i.e. SSPs: 245 and 585), and two time periods (the 2050s and 2070s) were targeted to seek the impact on habitat suitability variations of *M. buxifolia* on a temporal scale. The results predicted that all the future climate change options might remarkably influence the existing predicted probability of occurrence negatively. Hence, under all the studied future climate change scenarios, the ecological niche of the tree species is predicted to reduce enormously, especially from the present core geographical areas (Fig. 6 and Table 2). In addition to niche contraction, it is also detected that the core geographical areas (microhabitats) might become limited to northern parts of the study area only. These predictions for the future will test the dispersal and invasion capabilities of the tree species. Till now, no study has reported the invasive behavior of the species, and secondly, to invade the novel habitat as predicted, the species might need to cross Karakorum-Himalaya-Hindu Kush mountain ranges which might be an uphill task. However, the growing anthropogenic influence especially along the trade routes like China's One Belt One Road, and China Pakistan Economic Corridor projects might facilitate the species.

A total of about 51,810 km^2 of the geographical area is predicted a suitable habitat for the tree species under SSPs 245 of the 2050s, representing a change of −27% compared to current climate. Similarly, a change of −68%, −59%, and −107% were predicted under SSPs 585 in the 2050s, SSPs 245 in 2070s, and SSPs 585 in 2070s respectively. Hence, under all the studied future climate change scenarios, existing core areas of Pakistan are predicted to face the majority of impact. A negative rate of change was recorded for both Pakistan and Afghanistan under all future climate change options whereas a positive rate was noted for Jammu and Kashmir, India

Table 2
Potential distribution (area in km^2) of *M. buxifolia* in different habitat suitability classes (HSCs) under current and future climate change scenarios.

Climate scenario	Country	HSC-1 (p 0–0.2)	HSC-2 (p 0.2–0.4)	HSC-3 (p 0.4–0.6)	HSC-4 (p 0.6–0.8)	HSC-5 (p 0.8–1)	Total suitable area
Current climate	Afghanistan	643001	4546	3244	1816	253	9859
SSPs 245 (2050s)	Afghanistan	644649	4188	1893	1263	867	8211
Rate of change (%)		0	−8	−54	−36	123	−18
SSPs 585 (2050s)	Afghanistan	645715	3909	1639	1039	559	7145
Rate of change (%)		0	−15	−68	−56	79	−32
SSPs 245 (2070s)	Afghanistan	644803	4666	1537	1328	527	8057
Rate of change (%)		0	3	−75	−31	73	−20
SSPs 585 (2070s)	Afghanistan	647178	3509	1444	643	86	5682
Rate of change (%)		1	−26	−81	−104	−108	−55
Current climate	J&K, India	98537	2273	415	130	32	2850
SSPs 245 (2050s)	J&K, India	93686	5756	1229	496	219	7701
Rate of change (%)		−5	93	109	134	193	99
SSPs 585 (2050s)	J&K, India	97431	3006	594	251	105	3956
Rate of change (%)		−1	28	36	65	120	33
SSPs 245 (2070s)	J&K, India	97638	2715	654	264	116	3749
Rate of change (%)		−1	18	46	70	129	27
SSPs 585 (2070s)	J&K, India	99796	1387	162	31	10	1591
Rate of change (%)		1	−49	−94	−143	−112	−58
Current climate	Pakistan	826938	25130	12916	9889	7041	54975
SSPs 245 (2050s)	Pakistan	846014	16306	7397	5675	6520	35899
Rate of change (%)		2	−43	−56	−56	−8	−43
SSPs 585 (2050s)	Pakistan	858727	11722	6069	3685	1709	23186
Rate of change (%)		4	−76	−76	−99	−142	−86
SSPs 245 (2070s)	Pakistan	856170	13326	5674	4209	2534	25743
Rate of change (%)		3	−63	−82	−85	−102	−76
SSPs 585 (2070s)	Pakistan	866009	10597	3725	1302	281	15904
Rate of change (%)		5	−86	−124	−203	−322	−124
Current climate	Total	1568476	31949	16575	11835	7326	67684
SSPs 245 (2050s)	Total	1584350	26251	10519	7434	7606	51810
Rate of change (%)		1	−20	−45	−46	4	−27
SSPs 585 (2050s)	Total	1601872	18637	8302	4975	2374	34288
Rate of change (%)		2	−54	−69	−87	−113	−68
SSPs 245 (2070s)	Total	1598611	20707	7865	5800	3176	37549
Rate of change (%)		2	−43	−75	−71	−84	−59
SSPs 585 (2070s)	Total	1612982	15493	5331	1977	378	23178
Rate of change (%)		3	−72	−113	−179	−297	−107

depicting a northward shift of habitat suitability of the considered species (Fig. S3 and Table 2). All the pairwise inter-conversions of HSCs under projected future climate change options are presented in Fig. S3.

3.5. MESS analysis and ANOVA

Multivariate environmental similarity surfaces analysis was performed to seek the geographic distribution pattern of analogous environmental conditions for the considered tree species under future climate change scenarios (Fig. 7). The optimal environmental conditions in the study area are predicted to contract more and more in order from SSPs 245 in 2050s to SSPs 585 in 2070s, and reasonably match with the predicted probabilities of occurrences. The prediction probability values of the 75 occurrence sites of *M. buxifolia* comprising one current and four future climate changes scenarios were extracted. The significant difference among the group means of all the five climatic conditions was tested by using ANOVA. The results depicted that there was a significant (p-value <0.05; F value: 58.28) group mean difference, and post-hoc testing results depicted that the prediction probabilities might significantly dwindle under all the studied future climate change scenarios (Fig. 8). Hence, these variations in the predicted probabilities under projected future climatic variations might significantly affect the *M. buxifolia* distribution pattern, range, and niche shift in the study area.

4. Discussion

M. buxifolia is one of the economically important broad-leaved native tree species of Pakistan, and eastern adjoining parts of Afghanistan [37]. This tree species provides a wide range of ecosystem services (i.e. fruits, income source, fodder, fuel, fencing, etc.) to the local communities [25]. The illegal logging of the species is severely disrupting the local ecosystem's functioning for nearly a decade, and war and terror in this hotspot are further intensifying the issue [38]. Due to owing multiple usages, ever-increasing overexploitation has resulted in the rapid decline of the species population size, and local communities consequently lose linked ecosystem services [38,39]. Anthropogenic disturbances and climatic variations beyond the tolerance limit having intense effects on the population density of plant species [40,41]. The conservation of microhabitats supporting the valuable plant species is needed on an urgent basis for continuous and sustainable provisioning, and regulatory ecosystem services. Accordingly, this study was carried out

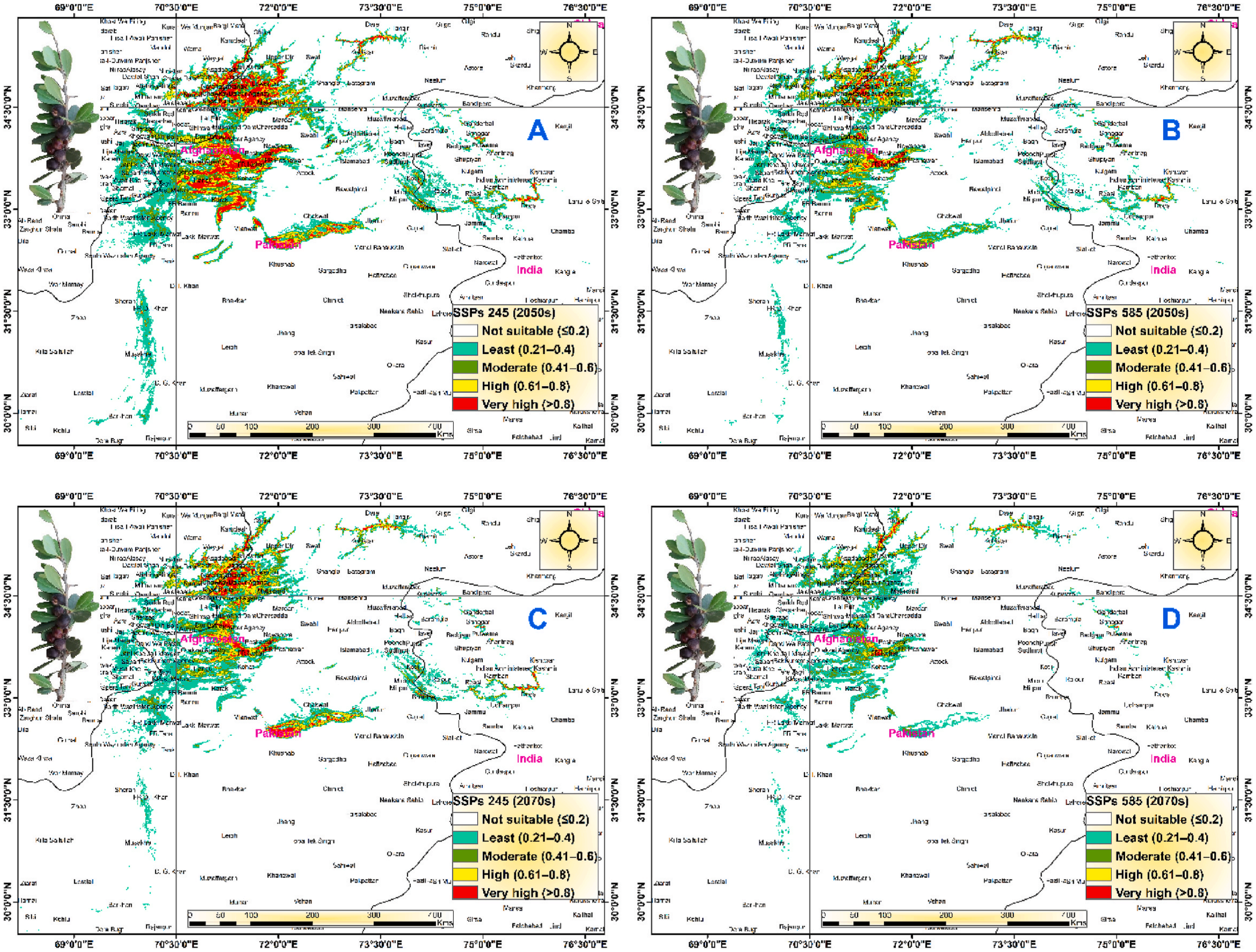

Fig. 6. Map displaying the impact of the considered future climate change scenarios on the potential distribution of *M. buxifolia* in the study area (A: SSPs 245 (the 2050s); B: SSPs 585 (2050s); C: SSPs 245 (2070s) and D: SSPs 585 (2070s)) Colors coding for each HSCs are same as in Fig. 5. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

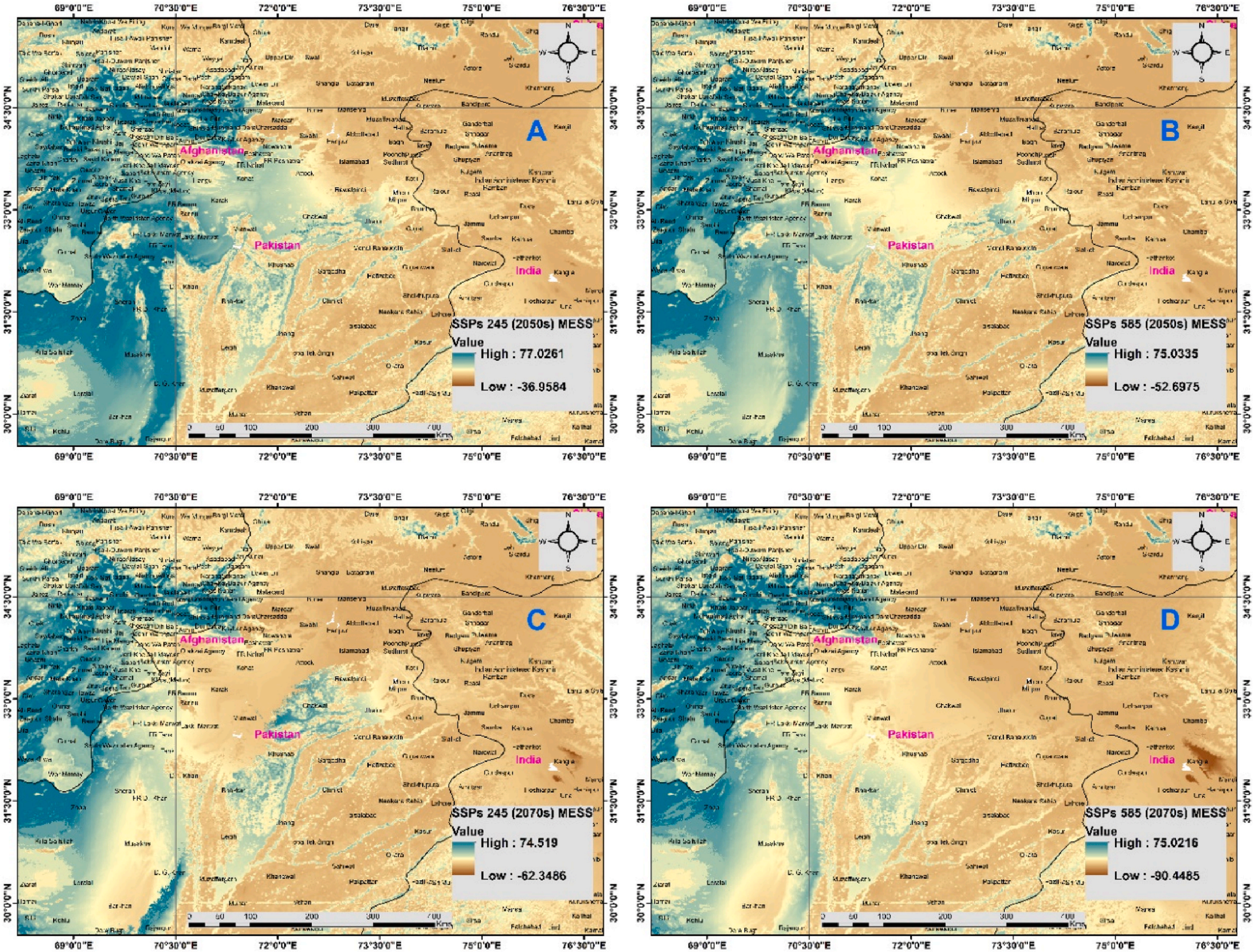

Fig. 7. Map depicting results of multivariate environmental similarity surfaces analysis for *M. buxifolia* under projected climate change scenarios in the study area (A: SSPs 245 (2050s); B: SSPs 585 (2050s); C: SSPs 245 (2070s) and D: SSPs 585 (2070s)).

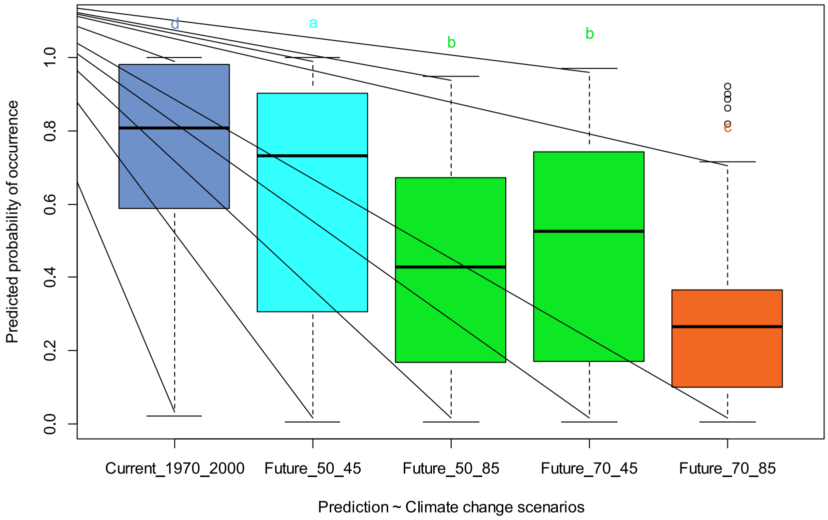

Fig. 8. Tukey's post-hoc test results depict the significant difference in the predicted probabilities of occurrences of *M. buxifolia* under different climate change scenarios at the studied locations.

to predict the potentially suitable habitat for *M. buxifolia* under varying climate change scenarios. Similar work of predicting suitable habitats has also reported on various plant species including *Olea ferruginea* [42], *Stipa purpurea* [6], *Taxus wallichiana* [32], *Juglans regia* [32].

Multiple machine learning distribution modelling algorithms like MaxEnt, RF, BRT and the ANN has been developed and used to identify the hotspot areas for conservation and management. These tools also help in developing a plan to mitigate the impact of predicted adverse future climate changes [34,43]. MaxEnt is the most suitable independent tool, even better than the ensemble modelling approach. By adjusting through tuning of RM values, it can avoid model overfitting, and work better in case of small sample size compared to other approaches [44]. It can capture required information even from the small non-linear data having complex interactions [45,46]. It is also comparatively impervious to a moderate degree of sampling bias [47], and presence-background data limitations [11,48]. Accordingly, this study opted for the use of the maximum entropy algorithm in MaxEnt to forecast the prediction probabilities for the considered tree species under current and projected future climate change scenarios. Additionally, another limitation of this study include; as this study targeted the potential distribution of the considered tree species from the core distribution areas only, the full climatic adaptability of the tree species needed to be explored to save the species in its entire native range.

On a regional scale, climate and topography are the leading factors that affect species abundance and distribution pattern, however, at the micro-environment level, physiochemical characteristics of the soil might be more important [3,49], or even interspecific competition, biological traits, and anthropogenic disturbances [50,51]. Similarly, interspecific relationships coupled with climate warming are also important drivers of the high upslope shift rate of the tree line in high elevation areas [52]. This study was focused on predicting the habitat suitability variations and mapping for the *M. buxifolia* under current and future potential climate change options (Figs. 5 and 6). SDM is mostly used to document, and predict the habitat suitability of conifers and evergreen broad-leaved tree species around the globe [53–55]. In all these studies, MaxEnt predictions were proved very informative under a variety of future climate change conditions. Based on the literature, this study utilized a total of 39 bioclimatic, topographic, edaphic, anthropogenic, and remote sensing variables to predict the habitat suitability of the considered tree species in the region. Such inclusion of a broad spectrum of predictor variables in the SDMs, might further enhance the accuracy of prediction [56]. Hence, SDM represents a useful macro-ecological tool to explore the interrelationships of environment and species distribution [54].

The performance of the predictive SDMs are evaluated by using multiple accuracy measures like AUC-ROC, TSS, Kappa statistics, pAUC-ROC, and AUC ratios. The first three measures are frequently criticized due to their dependence on prevalence [22], therefore, we use of multiple measures for comparative assessment. This study detected the pAUC-ROC values for the considered SDMs as > 0.9, and represent excellent model fit and performance. AUC-ROC value of more than 0.9 are also reported for *Taxus wallichiana* [53], *Acacia modesta* and *Pinus wallichian* [54], *Juglans regia* and *Taxus baccata* [21]. In spite of pAUC-ROC, AUC-ROC values are sensitive to the prevalence and extent of the study area, hence, should be interpreted carefully. Similarly, the number and types of predictor variables strongly influence the model output and are associated with model over-fitting. Similarly, model tuning, and search and use of optimal model settings is another important step in SDMs development.

The relative contributions of the predictor variables were assessed by using Jackknife tests (Fig. 4). Our results depicted that precipitation of the warmest quarter (Bio18: 30.3%), topographic diversity (Tdiv: 24.6%), global human modification of terrestrial land (gHM: 23.2%), NDVI (9.2%), isothermality (Bio3: 7.6%) and elevation (5.1%) (In order; Table 1) were the most influential drivers of predicted niche variations of the considered tree species. The role of these climatic variables are found very prominent in distribution of *Paeonia veitchii* species in China [57], which matches to the findings of this study. Precipitation of the warmest quarter was detected as the leading variable in the distribution of *Taxus wallichiana* [58]. Similarly, isothermality represents the proportion of mean diurnal range to annual temperature range. Hence, day and night, and summer and winter temperature differences strongly influence the considered tree species. This means that the predicted northwards niche shift for *M. buxifolia* in the Hindu Kush-Himalayan mountainous (HHM) region would be chiefly influenced by temperature and precipitation variation. Similar findings were also reported by Su et al. [59] and Li et al. [33], who communicated the role of temperature and precipitation factors in *Taxus wallichiana* distribution. Malekian and Sadeghi [60], reported the significant contribution of precipitation of the warmest quarter for Persian squirrel distribution in Iran. Similarly, topographic variables strongly influence the species distribution pattern either directly or indirectly via controlling soil moisture, radiation intensity, differential evapotranspiration, etc [1]. This study also recorded the prominent role of topographic diversity and elevation in niche variation of the considered tree species. Global human modification of terrestrial land dataset represents an index comprising intensity of land use land cover changes, traffic intensity, night-time lighting, infrastructure, industrial and mining activities [49,61], and a useful variable linked to anthropogenic activities. Additionally, NDVI variable is functionally more relevant to evaluate the forest plant species for their potential distribution under future climate change scenarios and often yield better model performance [62,63], which supports the findings of the current study.

Based on model predictions under the current climate scenario, this study has detected the majority of suitable habitats (locations with optimal environmental conditions for *M. buxifolia*) in Pakistan and Afghanistan. The same findings were reported by Ali et al. [4] while working on carbon stock of *M. buxifolia* forests along the altitudinal gradient in Pakistan. Species distribution modelling (SDM) and resultant habitat suitability maps are very important prerequisites for the conservation programs [63,64]. The findings of this study showed that the potential distribution and habitat suitability of *M. buxifolia* is very high in the north-western and north-eastern parts of Pakistan and Afghanistan respectively. Different districts of Pakistan like Dir Upper, Dir lower, Mohmand, Malakand, Bajaur, and Khyber were detected as very high suitability areas for *M. buxifolia*, and found in the Hindu Kush and Suleiman mountains ranges of the north-west of Pakistan. These core mountainous geographical areas have a very delicate ecosystem functioning, and adverse environmental changes can disrupt the balance and biodiversity.

This study targeted the predictive distribution modelling of *M. buxifolia* under projected future climate change options to seek influence on the species range, and possible niche shift as well. For this, a total of four future climate change scenarios (i.e. SSPs 245 and 585 of 2050s and 2070s) were targeted and included as future projections in the SDMs (Fig. 6 and Fig. S3). Such research work can help in mitigating the impact of predicted environmental changes, and assist in developing future conservation programs for the core geographical area to save biodiversity [22,32]. Geographical locations having optimal environmental conditions (with a high predicted probability of finding a species) should be given priority by developing biodiversity protection laws, and sustainable utilization should be ensured for species growth and survival. This study predicted that the ecological niche of the considered tree species might shrink remarkably, and simultaneously become limited to northern parts of the study area. It is also predicted that overall habitat suitability, as well as each considered HSCs, might remarkably dwindle under all considered future climate change scenarios in Pakistan. Similarly, the same pattern has been observed for Afghanistan except for HSC-5. However, an opposite pattern to Pakistan was recorded for Jammu and Kashmir, India, possibly due to a northwards shift of the ecological niche of the tree species (Fig. S3). This study recommends the strict implementation of biodiversity protection laws and policies to ensure the sustainable exploitation of wild resources. Despite the fact that Billion Tree Tsunami (BTT) afforestation/reforestation project has been initiated in KPK, Pakistan since 2014, this study recommends a coordinated multi-sectorial effort for conservation management, plantation/cultivation, and commercialization of biological resources [65]. This study also suggest the plantation of native *M. buxifolia* tree in the predicted highly suitable areas. This might result in better seedling growth and survival, and quick ecosystem restoration.

5. Conclusions

The predictive distribution modelling of *M. buxifolia* was performed considering current and future climate change scenarios (SSPs 245 and 585 of the 2050s and 2070s), and the maximum entropy algorithm. A total of 39 different environmental variables influencing the target tree species were included in SDMs, out of which six were detected with a leading influential role. The fitness of the model was evaluated by inspecting the pAUC-ROC value, and showed excellent (>0.9) prediction performance. At the moment, a total of about 67,684 km^2 geographic area is predicted as suitable for the considered tree species in Pakistan, Afghanistan and Jammu and Kashmir, India. Based on percent contribution of the predictor variables (in order), precipitation of warmest quarter (Bio18: 30.3%), topographic diversity (Tdiv: 24.6%), global human modification of terrestrial land (gHM: 23.2%), NDVI (9.2%), isothermality (Bio3: 7.6%) and elevation (5.1%) were detected with a leading role in driving niche variations of M. buxifolia. The north-western part of Khyber Pakhtunkhwa (allied to the Durand line or Pak-Afghan border) in Pakistan and north-eastern parts of Afghanistan are included among the core habitat of the considered species. Interestingly, the species is not reported from Jammu and Kashmir, India till now but comprised optimal environmental conditions in some parts, and a suitable geographic area is predicted to expand under considered future climate change scenarios depicting northward niche shift, whereas, an opposite trend was predicted for both Pakistan and Afghanistan. ANOVA results for the five considered climate groups depicted that the probability of the presence of the tree species at existing 75 study locations will significantly (p-value <0.05) dwindle under all future (the 2050s, 2070s) climate change scenarios (SSPs 245 and 585). Hence, development, and implementation of the appropriate conservation programs are required on a priority basis to save the tree species, especially in Pakistan. Such conservation efforts will not only save the tree species in their native area but also help in better socio-economic activities.

Author contributions

Fayaz Ali: Conceived and designed the experiments, performed the experiments, wrote the paper.
Nasrullah Khan: Conceived and designed the experiments, wrote the paper.
Arshad Mahmood Khan: Conceived and designed the experiments, analyzed and interpreted the data, Contributed reagents, materials, analysis tools or data, wrote the paper.
Kishwar Ali: Conceived and designed the experiments, wrote the paper.
Farhat Abbas: Contributed reagents, materials, analysis tools.

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Data availability statement

Data included in article/supp. material/referenced in article.

Declaration of interest's statement

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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.e13417.

References

[1] A.M. Khan, R. Qureshi, Z. Saqib, Multivariate analyses of the vegetation of the western Himalayan forests of Muzaffarabad district, Azad Jammu and Kashmir, Pakistan, Ecol. Indicat. 104 (2019) 723–736, https://doi.org/10.1016/j.ecolind.2019.05.0488.
[2] L.V. Sorokin, G. Mondello, Entering the New+ 2 C Global Warming Age and a Threat of World Ocean Expansion for Sustainable Economic Development, in: Climate Change, Extreme Events and Disaster Risk Reduction, Springer, Cham, 2018, pp. 183–201.
[3] F. Ali, N. Khan, K. Ali, M.E.H. Khan, D.A. Jones, Vegetation pattern and regeneration dynamics of the progressively declining *Monotheca buxifolia* forests in Pakistan: implications for conservation, Sustainability 14 (10) (2022) 6111, https://doi.org/10.3390/su14106111.
[4] F. Ali, N. Khan, E.F. Abd_Allah, A. Ahmad, Species diversity, growing stock variables and carbon mitigation potential in the phytocoenosis of *Monotheca buxifolia* forests along altitudinal gradient across Pakistan, Appl. Sci. 12 (3) (2022) 1292, https://doi.org/10.3390/app12031292.
[5] A.M. Khan, N. Khalid, Climate change is driving greening trend whereas tree cover is declining in the western Himalaya of Pakistan, J. Bioresour. Manag. 8 (2021) 1–26, https://doi.org/10.35691/JBM.1202.0200.
[6] B. Ma, J. Sun, Predicting the distribution of *Stipa purpurea* across the Tibetan plateau via the MaxEnt model, BMC Ecol. 18 (2018) 1–12, https://doi.org/10.1186/s12898-018-0165-0.
[7] R. Valavi, G. Guillera-Arroita, J.J. Lahoz-Monfort, J. Elith, Predictive performance of presence-only species distribution models: a benchmark study with reproducible code, Ecol. Monogr. 92 (1) (2022), e01486.
[8] I. Gómez-Undiano, F. Musavi, W.L. Mushobozi, G.M. David, R. Day, R. Early, K. Wilson, Predicting potential global and future distributions of the African armyworm (*Spodoptera exempta*) using species distribution models, Sci. Rep. 12 (1) (2022) 1–12, https://doi.org/10.1038/s41598-022-19983-y.
[9] H.S. Yuan, Y.L. Wei, X.G. Wang, Maxent modeling for predicting the potential distribution of Sanghuang, an important group of medicinal fungi in China Fungal, Fungal Ecol. 17 (2015) 140–145, https://doi.org/10.1016/j.funeco.2015.06.001.
[10] A. Khan, G.A. Bajwa, X. Yang, M. Hayat, J. Muhammad, F. Ali, A. Quddoos, A. Amin, T.U. Khan, A.U. Khan, Determining effect of tree on wheat growth and yield parameters at three tree-base distances in wheat/Jand (*Prosopis cineraria*) agroforestry systems, Agrofor. Syst. (2022) 1–10, https://doi.org/10.1007/s10457-022-00797-w.
[11] S.J. Phillips, R.P. Anderson, R.E. Schapire, Maximum entropy modeling of species geographic distributions, Ecol. Model. 190 (2006) 231–259, https://doi.org/10.1016/j.ecolmodel.2005.03.0266.
[12] J.N. Cardona, R.D. Loyola, Applying niche-based models to predict endangered-hylid potential distributions: are neotropical protected areas effective enough? Trop. Convers. Sci. 1 (2008) 417–445, https://doi.org/10.1177/194008290800100408.
[13] N. Dubos, C. Préau, M. Lenormand, G. Papuga, S. Monsarrat, P. Denelle, M. Le Louarn, S. Heremans, R. May, P. Roche, S. Luque, Assessing the effect of sample bias correction in species distribution models, Ecol. Indicat. 145 (2022), 109487.
[14] X.Q. Yang, S.P.S. Kushwaha, S. Saran, J. Xu, P.S. Roy, Maxent modeling for predicting the potential distribution of medicinal plant, *Justicia adhatoda* L. in Lesser Himalayan foothills, Ecol. Eng. 51 (2013) 83–87, https://doi.org/10.1016/j.ecoleng.2012.12.004.
[15] G.E. Hutchinson, Concluding remarks, Cold Spring Harbor Symp. Quant. Biol. 22 (1957) 415–427.
[16] T.H. Booth, H.A. Nix, J.R. Busby, M.F. Hutchinson, BIOCLIM: the first species distribution modelling package, its early applications and relevance to most current MAXENT studies, Divers. Distrib. 20 (1) (2014) 1–9, https://doi.org/10.1111/ddi.12144.

[17] R. Hijmans, S. Cameron, J. Parra, P. Jones, A. Jarvis, Very high resolution interpolated climate surfaces for global land areas, Int. J. Climatol. 25 (2005) 1965–1978, https://doi.org/10.1002/joc.1276.
[18] S.E. Fick, R.J. Hijmans, WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas, Int. J. Climatol. 37 (2017) 4302–4315, https://doi.org/10.1002/joc.5086.
[19] T.H. Booth, The Need for a Global Tree Trial Database, in: New Forests, 2022, pp. 1–7, https://doi.org/10.1007/s11056-022-09940-y.
[20] C.J. Ellis, Ancient woodland indicators signal the climate change risk for dispersal-limited species, Ecol. Indicat. 53 (2015) 106–114, https://doi.org/10.1016/j.ecolind.2015.01.028.
[21] W. Khan, M. Hussain, K. Ali, M. Ali, M. Nisar, Distribution and phenotypic variation in *Juglans regia* L. growing in Hindu Kush ranges of Pakistan, Acta Ecol. Sin. 40 (2020) 363–372, https://doi.org/10.1016/j.chnaes.2020.02.009.
[22] A.M. Khan, Q. Li, Z. Saqib, N. Khan, T. Habib, N. Khalid, A. Tariq, MaxEnt modelling and impact of climate change on habitat suitability variations of economically important Chilgoza pine (*Pinus gerardiana* Wall.) in South Asia, Forests 13 (5) (2022) 715, https://doi.org/10.3390/f13050715.
[23] F. Ali, N. Khan, Do environmental variables and overstory communities affect the spatial pattern of understory vegetation? Lessons from *Monotheca buxifolia* (Falc.) A. DC. forests in Pakistan, Acta Bot. Bras. 36 (2022), https://doi.org/10.1590/0102-z3062021abb0210.
[24] F. Ali, N. Khan, K. Ali, M. Amin, M.E.H. Khan, D.A. Jones, Assessment of variability in nutritional quality of wild edible fruit of *Monotheca buxifolia* (Falc.) A. DC. Along the altitudinal gradient in Pakistan, Saudi J. Biol. Sci. 30 (1) (2023), 103489.
[25] F. Ali, N. Khan, O. Rahmonov, Ecosystem services and linkages of naturally managed *Monotheca buxifolia* (Falc.) A. DC. Forests with local communities across contiguous mountainous ranges in Pakistan, Biology 11 (10) (2022) 1469, https://doi.org/10.3390/biology11101469.
[26] N. Khalid, A.M. Khan, R. Qureshi, Z. Saqib, N. Zahid, R.W. Bussmann, Exploration of important environmental determinants of flowering phenology in the western Himalayan forests of Dhirkot, Azad Jammu and Kashmir, Pakistan, Appl. Ecol. Environ. Res. 20 (1) (2022) 301–337, https://doi.org/10.15666/aeer/2001_301337.
[27] F. Ali, N. Khan, A. Ahmad, A.A. Khan, Structure and biomass carbon of *Olea ferruginea* forests in the foot hills of Malakand division, Hindukush range mountains of Pakistan, Acta Ecol. Sin. 39 (4) (2019) 261–266, https://doi.org/10.1016/j.chnaes.2019.05.011.
[28] K.A. Ryniker, J.K. Bush, O.V. Auken, Structure of *Quercus gambelii* communities in the lincoln national forest New Mexico, USA, For. Ecol. Manag. 233 (2006) 69–77, https://doi.org/10.1016/j.foreco.2006.06.008.
[29] C.M. Kennedy, J.R. Oakleaf, D.M. Theobald, S. Baruch-Mordo, J. Kiesecker, Documentation for the Global Human Modification of Terrestrial Systems, NASA Socioeconomic Data and Applications Center (SEDAC), Palisades, NY, 2020, https://doi.org/10.7927/jw1p-am22.
[30] R. Muscarella, P.J. Galante, M. Soley-Guardia, R.A. Boria, J. Kass, M. Uriarte, R.P. Anderson, ENMeval: an R package for conducting spatially independent evaluations and estimating optimal model complexity for ecological niche models, Methods Ecol. Evol. 5 (2014) 1198–1205, https://doi.org/10.1111/2041-210X.12261.
[31] H. Gilani, M.A. Goheer, H. Ahmad, K. Hussain, Under predicted climate change: distribution and ecological niche modelling of six native tree species in Gilgit-Baltistan, Pakistan, Ecol. Indicat. 111 (2020), 106049, https://doi.org/10.1016/j.ecolind.2019.106049.
[32] Y. Li, M. Li, C. Li, Z. Liu, Optimized maxent model predictions of climate change impacts on the suitable distribution of *Cunninghamia lanceolata* in China, Forests 11 (3) (2020) 302, https://doi.org/10.3390/f11030302.
[33] P. Li, W. Zhu, Z. Xie, K. Qiao, Integration of multiple climate models to predict range shifts and identify management priorities of the endangered *Taxus wallichiana* in the Himalaya–Hengduan Mountain region, J. For. Res. 31 (2019) 2255–2272, https://doi.org/10.1007/s11676-019-01009-5.
[34] J. Elith, et al., Novel methods improve prediction of species distributions from occurrence data, Ecography 29 (2006) 129–151, https://doi.org/10.1111/j.2006.0906-7590.04596.x.
[35] A. Radosavljevic, R.P. Anderson, M. Araújo, Making better MaxEnt models of species distributions: complexity, overfitting and evaluation, J. Biogeogr. 41 (2014) 629–643, https://doi.org/10.1111/jbi.12227.
[36] A.M. Khan, R. Qureshi, Z. Saqib, T. Habib, M. Ilyas, M. Maqsood, R. Kosar, M. Akram, B.Z. Rahim, A.M. Khan, R. Qureshi, M. Arshad, S.N. Mirza, A novel study of the interrelationship of seasonality, satellite data and weed compositional changes of the agro-ecological system of Gujrat, Pakistan, Appl. Ecol. Environ. Res. 16 (2018) 2995–3018, https://doi.org/10.15666/aeer/1603_29953018.
[37] N. Khan, F. Ali, K. Ali, S. Shaukat, Composition, structure and regeneration dynamics of *Olea ferruginea* Royle forests from Hindukush range of Pakistan, J. Mt. Sci. 12 (2015) 647–658, https://doi.org/10.1007/s11629-013-2831-1.
[38] F. Ali, N. Khan, K. Ali, I. Khan, Influence of environmental variables on the distribution of woody species in Muslim graveyards of Malakand division, Hindukush range mountains of Pakistan, Pakistan J. Bot. 49 (2017) 2357–2366.
[39] M. Amin, A.R. Gurmani, F. Ali, S.M. Khan, A. Farid, M. Shakur, W. Khan, Investigation of multi-pesticide residues in *Prunus persica* L.(peach) cultivars of district Swat using gas chromatography-mass spectroscopy, Pol. J. Environ. Stud. 31 (2022) 1535–1542, https://doi.org/10.15244/pjoes/141808.
[40] T. Iqbal, T. Habib, K. Hussain, A.M. Khan, Wild edible plant basket of terrestrial paradise and variations among the diverse ethnic and elevation groups–A detailed insight from the western Himalaya of Azad Jammu and Kashmir, Pakistan, S. Afr. J. Bot. 147 (2022) 294–313, https://doi.org/10.1016/j.sajb.2022.01.026.
[41] M. Munir, S. Sadia, A. Khan, B.Z. Rahim, B. Gagosh Nayyar, K.S. Ahmad, R. Qureshi, Ethnobotanical study of Mandi Ahmad Abad, district Okara, Pakistan, PLoS One 17 (4) (2022), e0265125, https://doi.org/10.1371/journal.pone.0265125.
[42] U. Ashraf, H. Ali, M.N. Chaudry, I. Ashraf, A. Batool, Z. Saqib, Predicting the potential distribution of *Olea ferruginea* in Pakistan incorporating climate change by using Maxent model, Sustainability 8 (2016) 722, https://doi.org/10.3390/su8080722.
[43] A. Norberg, N. Abrego, F.G. Blanchet, F.R. Adler, B.J. Anderson, J. Anttila, M.B. Araújo, T. Dallas, D. Dunson, J. Elith, et al., A comprehensive evaluation of predictive performance of 33 species distribution models at species and community levels, Ecol. Monogr. 89 (2019), e01370, https://doi.org/10.1002/ecm.1370.
[44] E. Kaky, V. Nolan, A. Alatawi, F. Gilbert, A comparison between Ensemble and MaxEnt species distribution modelling approaches for conservation: a case study with Egyptian medicinal plants, Ecol. Inf. 60 (2020), 101150, https://doi.org/10.1016/j.ecoinf.2020.101150.
[45] M. Abdelaal, M. Fois, G. Fenu, G. Bacchetta, Using MaxEnt modeling to predict the potential distribution of the endemic plant Rosa arabica Crép. in Egypt, Ecol. Inf. 50 (2019) 68–75, https://doi.org/10.1016/j.ecoinf.2019.01.003.
[46] E. Kaky, F. Gilbert, Allowing for human socioeconomic impacts in the conservation of plants under climate change, Plant Biosyst. 154 (2019) 295–305, https://doi.org/10.1080/11263504.2019.1610109.
[47] C.H. Graham, J. Elith, R.J. Hijmans, A. Guisan, A.T. Peterson, B.A. Loiselle, The influence of spatial errors in species occurrence data used in distribution models, J. Appl. Ecol. 45 (2008) 239–247, https://doi.org/10.1111/j.1365-2664.2007.01408.x.
[48] R.A. Baldwin, Use of maximum entropy modeling in wildlife research, Entropy 11 (2009) 854–866, https://doi.org/10.3390/e11040854.
[49] M. Majeed, A.M. Khan, T. Habib, M.M. Anwar, H.A. Sahito, N. Khan, K. Ali, Vegetation analysis and environmental indicators of an arid tropical forest ecosystem of Pakistan, Ecol. Indicat. 142 (2022), 109291, https://doi.org/10.1016/j.ecolind.2022.109291.
[50] Y. Liang, M.J. Duveneck, E.J. Gustafson, J.M. Serra-Diaz, J.R. Thompson, How disturbance, competition, and dispersal interact to prevent tree range boundaries from keeping pace with climate change, Global Change Biol. 24 (2018) e335, https://doi.org/10.1111/gcb.13847. –e351.
[51] W.J. Wang, H.S. He, F.R. Thompson, M.A. Spetich, J.S. Fraser, Effects of species biological traits and environmental heterogeneity on simulated tree species distribution shifts under climate change, Sci. Total Environ. 634 (2018) 1214–1221, https://doi.org/10.1016/j.scitotenv.2018.03.353.
[52] E.Y. Liang, Y.F. Wang, S.L. Piao, X.M. Lu, J.J. Camarero, H.F. Zhu, L.P. Zhu, A.M. Ellison, P. Ciais, J. Peñuelas, Species interactions slow warming-induced upward shifts of treelines on the Tibetan Plateau, Proc. Natl. Acad. Sci. USA 113 (2016) 4380–4385, https://doi.org/10.1073/pnas.1520582113.
[53] J.P. Gajurel, S. Werth, K.K. Shrestha, C. Scheidegger, Species distribution modeling of *Taxus wallichiana* (Himalayan Yew) in Nepal Himalaya, Asian. J. Conserv. Biol. 3 (2014) 127–134.
[54] G. Guillera-Arroita, J. Lahoz-Monfort, J. Elith, MaxEnt is not a presence absence method: a comment on Thibaud et al, Methods Ecol. Evol. 5 (2014) 1192–1197, https://doi.org/10.1111/2041-210X.12252.

[55] K. Ali, H.A. Begum, A comparative assessment of climate change effect on some of the important tree species of Hindu-Kush Himalayas, using predictive modelling techniques, Int. J. Adv. Res. 3 (2015) 1230–1240, https://doi.org/10.15242/IICBE.C0415015.
[56] M.C. Urban, G. Bocedi, A.P. Hendry, J.B. Mihoub, et al., Improving the forecast for biodiversity under climate change, Science 353 (2016), https://doi.org/10.1126/science.aad8466.
[57] K. Zhang, Y. Zhang, J. Tao, Predicting the potential distribution of *Paeonia veitchii* (Paeoniaceae) in China by incorporating climate change into a Maxent model, Forests 10 (2019) 190, https://doi.org/10.3390/f10020190.
[58] P. Rathore, A. Roy, H. Karnatak, Modelling the vulnerability of *Taxus wallichiana* to climate change scenarios in South East Asia, Ecol. Indicat. 102 (2019) 199–207, https://doi.org/10.1016/j.ecolind.2019.02.020.
[59] J.R. Su, Z.J. Zhang, J. Deng, G.S. Li, Relationships between geographical distribution of *Taxus wallichiana* and climate in China, For. Res. 18 (2005) 510–515.
[60] M. Malekian, M. Sadehgi, Predicting impacts of climate change on the potential distribution of two interacting species in the forests of western Iran, Meteorol. Appl. (2019) 1–10, https://doi.org/10.1002/met.1800.
[61] M.N. Awan, et al., Using ensemble modeling to predict breeding habitat of the red-listed Western Tragopan (*Tragopan melanocephalus*) in the Western Himalayas of Pakistan, – *Glob. Ecol. Conserv*. 31 (2021), e01864, https://doi.org/10.1016/j.gecco.2021.e01864.
[62] D. Adhikari, Z. Reshi, B.K. Datta, S.S. Samant, A. Chettri, K. Upadhaya, S.K. Barik, Inventory and characterization of new populations through ecological niche modelling improve threat assessment, Curr. Sci. 2018 (2018) 519–531.
[63] B.M. Benito, L. Cayuela, F.S. Albuquerque, The impact of modelling choices in the predictive performance of richness maps derived from species-distribution models: guidelines to build better diversity models, Methods Ecol. Evol. 4 (2013) 327–335, https://doi.org/10.1111/2041-210x.12022.
[64] T. Distler, J.G. Schuetz, J. Velásquez-Tibatá, G.M. Langham, Stacked species distribution models and macroecological models provide congruent projections of avian species richness under climate change, J. Biogeogr. 42 (2015) 976–988, https://doi.org/10.1111/jbi.12479.
[65] J. Duque-Lazo, R.M. Navarro-Cerrillo, F.J. Ruı′z-Go′mez, Assessment of the future stability of cork oak (*Quercus suber* L.) afforestation under climate change scenarios in Southwest Spain, For. Ecol. Manag. 409 (2018) 444–456, https://doi.org/10.1016/j.foreco.2017.11.042.