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RESEARCH ARTICLE

Distribution mapping of *Bauhinia vahlii* Wight & Arn. in India using ecological niche modelling

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Abstract

Bauhinia vahlii Wight & Arn. is an important multipurpose, woody climber used by the rural communities in India for various economic activities as well as for medicinal purposes. Indiscriminate extraction of the woody climber has led to population decline in its distribution range. Climate change has further led to the amplification leading to drastic decline of the natural populations. Therefore, the present study aimed to map the potential distribution of *B. vahlii* in India using ecological niche modelling (ENM) tools for the current and future climate change scenarios using RCP 2.6 and RCP 8.5. The maximum entropy model was performed using presence-only data of a total of 38 non-overlapping occurrence points obtained from multiple authenticated online portals and through a detailed field investigation. A rise in very high probable zones was observed under both the future climate change scenarios by 0.2% (RCP 2.6) and 0.5% (RCP 8.5) area increase compared to the current climatic scenario. The areas of moderately probable zones pose an increase by 4.5% in RCP 2.6 and a slight decrease by 0.4% in RCP 8.5, while the least probable zones were found to be decreasing in both the cases by 7.3% and 3.6%, respectively. It is predicted that *B. vahlii* will respond variably under different climate change scenarios based on the species' response to the variations in bioclimatic variables. The predicted impacts of climate change need to be integrated for conservation and management of this economically important, multipurpose woody climber. There is an urgent need for immediate policy intervention and implementation to save this species from the increasing anthropogenic pressure for various economic purposes.

Keywords Climate change scenarios · MaxEnt · Population mapping · RCP 2.6 · RCP 8.5

Introduction

Tropical forests have great ecological significance as they provide a range of ecological products and services, including conservation of terrestrial biodiversity, prevention of soil erosion, regulation of climate, cycling of nutrients, and habitat for wildlife (Retana et al. 2009; Kumar and Saikia 2020; Tiwari et al. 2021). Potential evapo-transpiration, or mean temperature and precipitation, chlorophyll density, climatic and topographic heterogeneity, ecological disturbances, and geographic constraints are the major determinants of forest structure and species' spatio-temporal distribution (Gelfand et al. 2006; Lal et al. 2021). Climate is considered one of the prime factors responsible for species potential distribution, and any alteration in it, impacts the ecosystem structure, functioning (Parmesan and Yohe 2003; Feeley et al. 2012), and shift in species' geographical distribution throughout the globe as species always tend to inhabit the most suitable habitat (Andrewartha and Birch 1954; Peterson 2003; Thomas et al. 2004; Loarie et al. 2008; Stevnbak et al. 2009). In tropical zones, the rising temperature might push species towards higher altitudes leading to shrinkage in the species (Peh 2007; Seimon et al. 2007; Chen et al. 2009). The global rise of 0.078 °C temperature was evident over the duration of 2003–2013, and an increment of 0.3–4.8 °C is projected

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by 2090–2099 (IPCC 2013), which may lead to habitat shifts and the risk of species extinction (Urban 2015).

Species distribution models (SDMs) also known as ecological niche models (ENMs) are scientifically proven tools for identifying the species' suitable habitat under current and future climate change scenarios that combine species occurrences with environmental variables to predict the possible distribution of a species (Franklin 2010). The ENMs predict a species' possible geographical distributions by relating the known occurrence of the species records with environmental layers (Grinnell 1917, 1924; de Siqueira et al. 2009). The ENMs are known for producing statistically robust predictions of species distribution, even in areas that are not sampled (Peterson 2006). These techniques are being used in many aspects of resource management, conservation planning (Joshi et al. 2017) including locating marginal populations of rare and threatened species (Guisan et al. 2013; Sumangala et al. 2017) and their habitats (Priti et al. 2016), justifying the selection of unknown habitat for the reintroduction of species (Polak and Saltz 2011; Nagaraju et al. 2013), invasive species risk assessment (Peterson 2003; Sen et al. 2016a; Shrestha et al. 2018), agricultural disease, insect pest forecasting (Murray et al. 2011), predicting the crop infestation (Ganeshaiah et al. 2003), and also in investigating and estimating the responses of species to global climate change (Sen et al. 2016b; Subba et al. 2018). Several modelling algorithms are available for SDMs to predict the species distribution pattern such as bioclimatic modelling (BIOCLIM, Busby 1991), boosted regression trees (BRT, Friedman 2000), climate change experiment (CLIMEX, Sutherst 1995), domain environmental envelope (DOMAIN, Carpenter et al. 1993), generalized linear model (GLM, Lehmann et al. 2002), generalized additive model (GAM, Yee and Mitchell 1991), genetic algorithm for rule-set production (GARP, Stockwell 1999), Multivariate adaptive regression splines (MARS, Thuiller et al. 2009), and Maximum Entropy (MAXENT, Phillips et al. 2006) and the performance of each algorithm varies significantly (Elith et al. 2010).

Among these algorithms, MaxEnt is widely used because of its various advantages: (1) MaxEnt is a general-purpose machine learning algorithm applied for generating species habitat suitability maps using presence-only data sets (Phillips et al. 2006). (2) Ability to handle small data sets and perform relatively better than other modelling algorithms (Pearson et al. 2007; Phillips and Dudik 2008). (3) The relative contribution of individual environmental variables to the modelling was evaluated using the Jack-knife test (Elith et al. 2011). (4) Maxent can handle both continuous and categorical input variables (Phillips et al. 2006). It has been used to predict the potential distribution of medicinal plants (Sharma et al. 2018), invasive alien plant species (Thapa et al. 2018), endemic frogs (Becerra Lopez et al. 2017), and birds (Singh et al. 2020). Map obtained with the help of the ENM tool (MaxEnt) represents the fundamental niche of the target species (Hutchinson 1957; Soberon and Peterson 2005).

Bauhinia vahlii Wight & Arn. is an evergreen woody climber (liana), native to the Indian subcontinent, and distributed in Asian countries, including Bhutan, India, Mauritius, Nepal, Pakistan, Sri Lanka, and Africa (Zaire) (Bisby 1994; Roskov et al. 2019). It is found in the lower Himalayas (up to altitudes of 1500 m), widely distributed in the deciduous forests of western to southern India, primarily in the hilly forest regions (Parrotta 2001) commonly occurred in the states of Punjab, Uttar Pradesh, West Bengal, Bihar, Assam, Maharashtra, Odisha, Andhra Pradesh, Karnataka, Tamil Nadu, J&K, Himachal Pradesh, Uttarakhand, and Sikkim (Parrotta 2001; Sankara et al. 2019). The climber is medicinally important, yields tanning material, grown as an ornamental plant, and serves numerous livelihood options to the rural populations throughout India (Nadkarni 1954). The local tribes of eastern India (Jharkhand and Odisha) use the broad leaves of *B. vahlii* for plate making, which is marketed as one of the common economic commodities in Indian rural markets (Mishra and Teki 2007). They collect it mostly during drought years when the economic support from regular crops is less (Gupta 2005). Unsustainable harvesting of the species from the wild, overgrazing, other biotic interferences, and climate change are considered significant threats to the species survival and leading to drastic decline of the natural populations of *B. vahlii*. Therefore, in the present study, we used maximum entropy modelling (MaxEnt) using occurrence data of *B. vahlii* (1) to map its potential distribution in tropical forests of India in the current scenario, and (2) to predict the impacts of future climatic changes on its possible distribution pattern regarding RCP 2.6 and RCP 8.5, which can further be used for effective management of the species.

Materials and methods

Studied plant species

Bauhinia vahlii is the gigantic woody climber belonging to the legume family Caesalpiniaceae, common in India and can grow up to 10 to 30 m long, with a girth of 20 cm. The foliage is used in thatching, mat making, packaging of food items, and tobacco wrapping (Manandhar 2002; Nadkarni 2005) and also as fodder, bark yields useful fibers for rope making, the matured cooked seeds are edible, and used by many tribal populations including Kondakapulu, Baagethalu, Munari in India (Rajaram and Janardhanan 1991; Vadivel and Janardhanan 2000). The pods and tender leaves are eaten as vegetables and the thick liquid obtained after boiling the leaves is used to treat dysentery and diarrhea (Kandhasamy and Kang 2013).

Species occurrence dataset

A total of 111 occurrence points were collected from multiple authenticated scientific sources. Fifty-seven occurrence records were obtained from Global Biodiversity Information Facility (GBIF) database (www.gbif.org, accessed 4 February 2020), 19 from published books, scientific journals, reports, India Biodiversity Portal (Rajaram and Janardhanan 1991; Upreti and Dhar 1996; Dhar and Upreti 1999; Samant et al. 2000, 2006; Patole and Jain 2002; Prasad and Nautiyal 2003; Pattanaik et al. 2007; Reddy and Ugle 2008; Dugasani et al. 2010; Sowndhararajan et al. 2010; Tiwari et al. 2010; Kandi et al. 2011; Das et al. 2012; Mishra and Chaudhury 2012; Bagchi and Banerjee 2013; Rajesh et al. 2013; Sowndhararajan and Kang 2013; Mastan et al. 2015), and 35 through field sampling using Garmin GPS device in western parts (Gumla and Latehar districts) of Jharkhand, India. A total of 12 belt transects, each of 0.1 ha size, were laid in the representative areas of the forests of western Jharkhand during January 2020. The datasets comprising occurrence records belonging to herbaria, museums, and geographical sampling are prone to sampling biases (Hijmans et al. 2000; Reddy and Davalos 2003; Graham et al. 2004; Kadmon et al. 2004; Hijmans 2012), and hence, addressing the effects of sampling biases becomes a priority. After applying spThin (Aiello-Lammens et al. 2015) function, 38 non-overlapping occurrence records were derived to run the model (Fig. 1).

Bioclimatic predictors

Nineteen bioclimatic variables were downloaded from the WorldClim database *Version* 1.4 (http://www.worldclim.org) (Hijmans et al. 2005). These variables were computed on various scales in terms of duration and maximum-minimum values for temperature and precipitation from 1950 to 2000 (Hamid et al. 2019). Altitude data (SRTM-DEM) was downloaded from the USGS

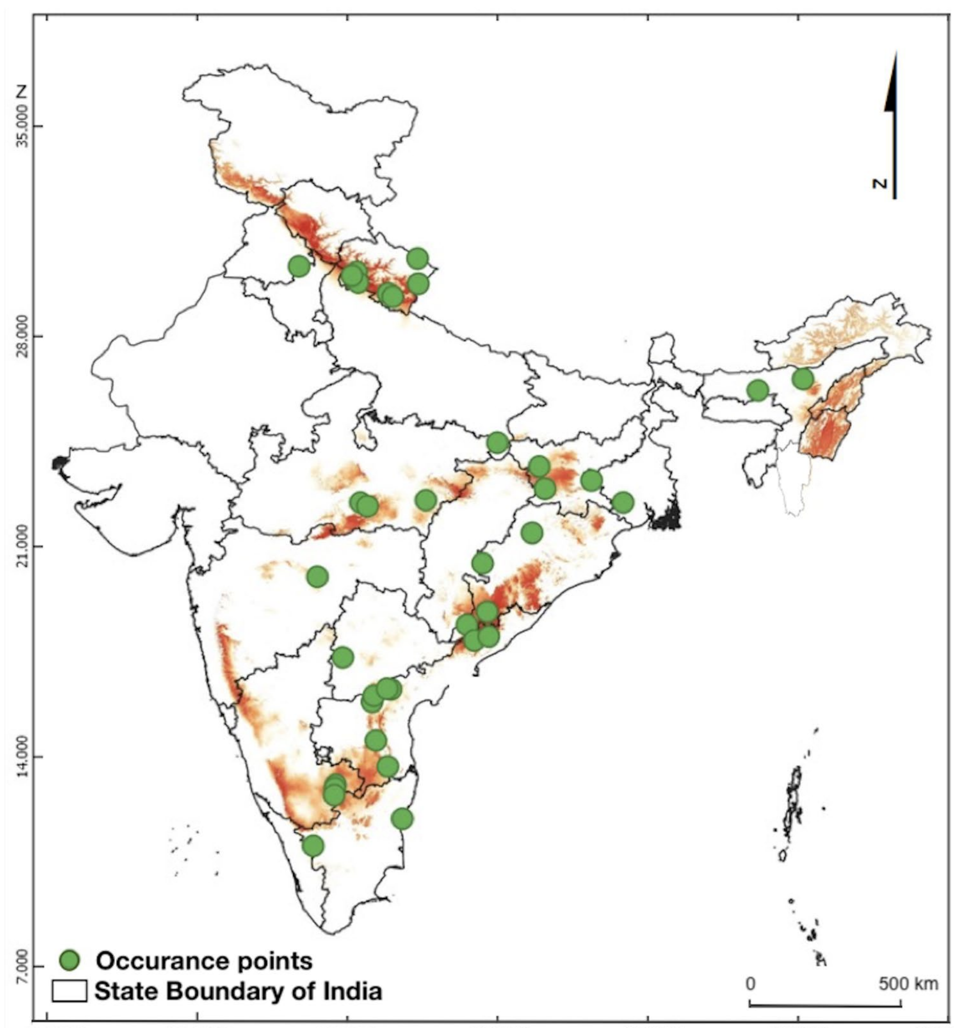

Fig. 1 Map showing the 38 occurrence points of *B. vahlii* derived from various sources

website (http://srtm.usgs.gov/index.php, Accessed on 20th January 2020). The highly correlated nature of these variables affects the model's performance and misleads the interpretation (Dormann et al. 2013). Therefore, Pearson-correlation analysis was performed to identify the highly correlated variables, *i.e.,* coefficient value ($r > 0.7$). Finally, 07 bioclimatic variables were retained to run the model from the whole list of 20 (Table 1).

Ecological niche modelling

Several distribution models have been introduced to provide precise information associated with the species distribution in response to changing climatic scenarios, including GLM, GAM, BRT, BIOCLIM, CLIMEX, GARP, and MaxEnt (Hill 1987; Bellard et al. 2012). The present study used the Maximum Entropy (MaxEnt) (Phillips et al. 2009) model with the Maxent algorithm (*version* 3.4.4) downloaded from (https://biodiversityinformatics.amnh.org/open_source/maxent/) (Steven and Phillips 2009) to map the potential distribution of *B. vahlii* in the tropical forests of India in current as well as for future climate change scenarios, *i.e.* RCP 2.6 and RCP 8.5. The detailed methodology flowchart is given in Fig. 2.

The intergovernmental panel on climate change (IPCC) data for two different future climatic change scenarios (Moss et al. 2010) were implemented to study the potential distribution of *B. vahlii* across the study area. While there are other scenarios available, only two extreme scenarios were taken for the analysis. These are the Representative Concentration Pathway (RCP) scenarios, RCP 2.6 and RCP 8.5 for the year 2050 and 2070 (based on the emission of greenhouse gases in the near future). RCP 2.6 represents the minimum greenhouse gas emission scenario, whereas RCP 8.5 represents maximum greenhouse gas emission scenario (IPCC 2014). RCP 2.6 is a very stringent pathway and assumes that carbon dioxide emissions would start declining by 2020 and go to zero by 2100. It also assumes that carbon dioxide emissions would decline to approximately 10% of those of 1980–1990. RCP 2.6 is likely to keep global temperature rise below 2 °C by 2100. However, the RCP 8.5 is a worst-case scenario and assumes that the emissions continue to rise throughout the twenty-first century. Though the RCP 8.5 scenario may be relatively unlikely, it remains useful for its aptness in both tracking total cumulative CO_2 emissions and in predicting mid-century emissions based on current and stated policies. MaxEnt is the best among 16 algorithms using presence-only data in terms of performance (Elith et al. 2006; Wisz et al. 2008), producing reliable and authenticate results with less, and unorganized sample data with slight location errors (Elith et al. 2006).

Model settings

In order to generate the model, 75% of the occurrence data were used for model training and the remaining 25% were used for model testing. Maxent model generates the

Table 1 Environmental variables used for Ecological Niche Modelling of *B. vahlii.* (Source: O'Donnell and Ignizio 2012)

Environmental Variables	
Alt	Altitude (m)
Bio_1	Annual Mean Temperature (℃)
Bio_2	Mean Diurnal Range (Mean of monthly (max temp—min temp) (℃)
Bio_3	Isothermality (Bio_2/ Bio_7) (* 100) (%)
Bio_4	Temperature Seasonality (standard deviation *100) (%)
Bio_5	Max Temperature of Warmest Month (℃)
Bio_6	Min Temperature of Coldest Month (℃)
Bio_7	Temperature Annual Range (Bio_5-Bio_6) (℃)
Bio_8	Mean Temperature of Wettest Quarter (℃)
Bio_9	Mean Temperature of Driest Quarter (℃)
Bio_10	Mean Temperature of Warmest Quarter (℃)
Bio_11	Mean Temperature of Coldest Quarter (℃)
Bio_12	Annual Precipitation (mm)
Bio_13	Precipitation of Wettest Month (mm)
Bio_14	Precipitation of Driest Month (mm)
Bio_15	Precipitation Seasonality (Coefficient of Variation) (mm)
Bio_16	Precipitation of Wettest Quarter (mm)
Bio_17	Precipitation of Driest Quarter (mm)
Bio_18	Precipitation of Warmest Quarter (mm)
Bio_19	Precipitation of Coldest Quarter (mm)

The highlighted variables were selected to model the potential distribution of *B. vahlii*

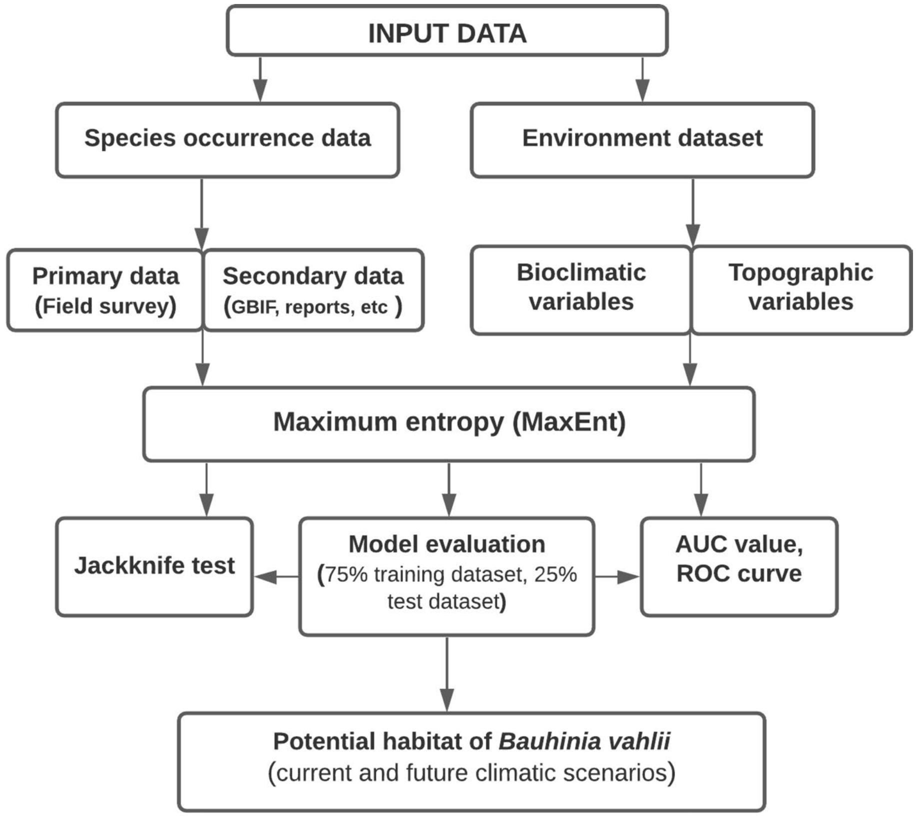

Fig. 2 Methodology flow chart summarizing the methodology used in modeling the suitable habitat of *B. vahlii*. AUC-ROC: area under the receiver operating characteristic curve

background environmental data (absence data) for the entire study area by setting the number of background points to 10,000 (Merow et al. 2013). The model was run in a subsample replicate type with 15 replicated runs. The MaxEnt model was run with the following default settings; number of iterations = 5000, output format = logistic, convergence threshold = 0.00001 and regularization multiplier = 1.

Performance evaluation

The model assessment was done by using the measurement of area under curve (AUC) of receiver operating characteristics (ROC) curve. The ROC curve was obtained after all the runs, showing the intermediate representation (Fig. 3). The graph was plotted between sensitivity and 1- specificity. Sensitivity provides an estimate of how readily the algorithm is correctly predicting the records of occurrence, whereas specificity offers an estimate of how readily it expects the absence records (Pearce and Ferrier 2000). The value of AUC ranges from 0 to 1, value lying between 0–0.5 indicates worse model prediction than random, 0.5–0.7 indicates poor, whereas 0.7–0.9 symbolizes a reasonable and moderate future level, and more than 0.9 defines the model performance to be high (Peterson et al. 2011).

Variable importance

Bioclimatic variables play a significant role in species distribution, and hence an assessment of the percentage contribution of the selected variables is mandatory. The jackknife test (Phillips 2017) results rank the bioclimatic variables based on their contribution to the modelling process.

Distribution area calculation

The output format was set as "logistics" to obtain probabilities (between 0 and 1) but scaled up in a non-linear manner for more straightforward interpretation. Further, numerical analysis was performed with the help of Microsoft Excel and DIVA-GIS (Hijmans et al. 2001), while mapping was done with the use of QGIS (*ver*. 3.10.1).

Results

Model performance

The area under curve (AUC) for both training and test data and the standard deviation in all three scenarios were obtained in the final Maxent output (Table 2). The MaxEnt model performance was evaluated based on AUC values. The AUC values were found to be > 0.8 for both training and

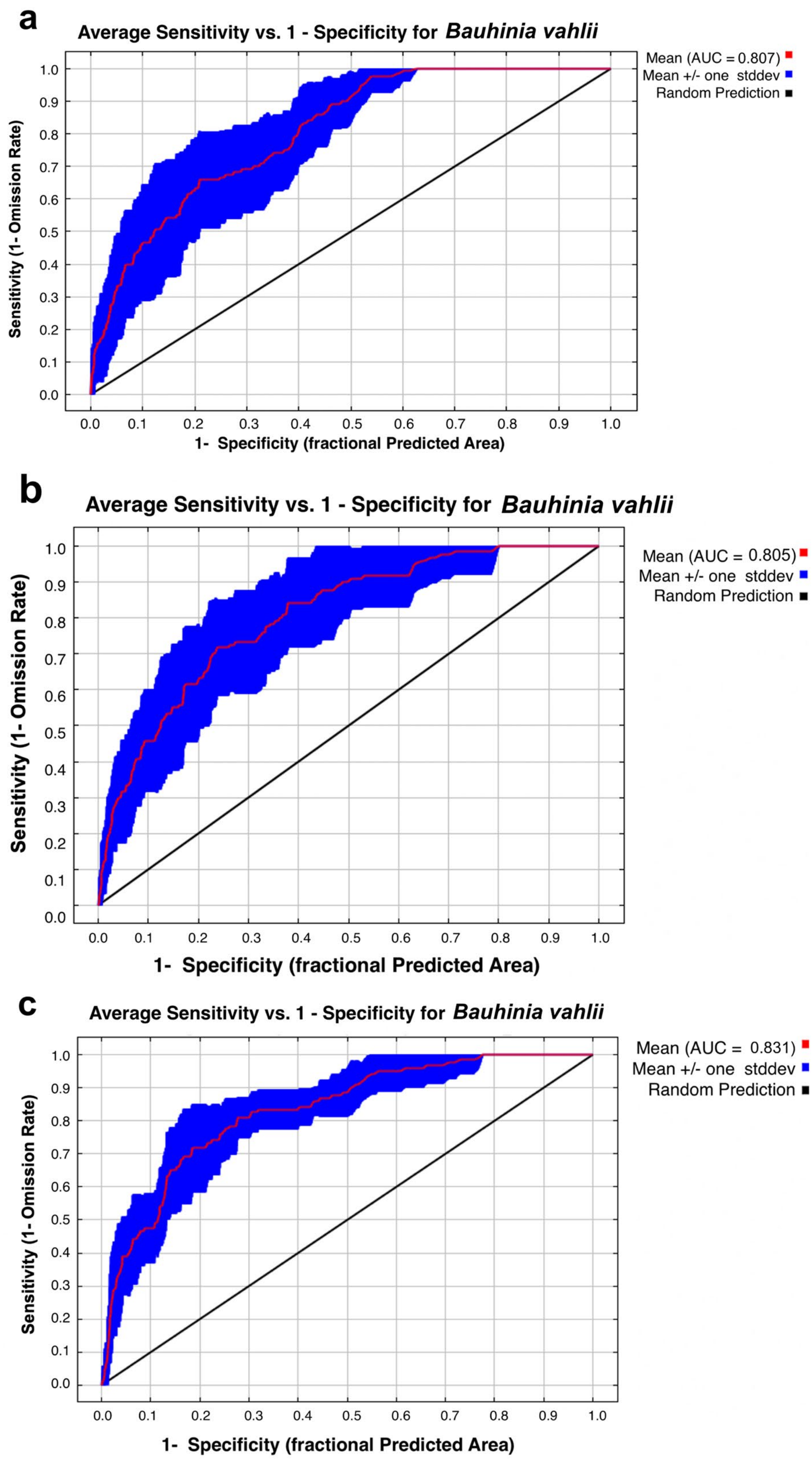

Fig. 3 Results of the Receiver Operating Characteristic (ROC) curve in developing *B. vahlii* habitat suitability model under **a** Current, **b** RCP 2.6, and **c** RCP 8.5 climatic scenarios

Table 2 Area Under Curve (AUC) ± Standard Deviation (SD) under current, RCP 2.6, and RCP 8.5 scenarios

	No. of points	Current	RCP 2.6	RCP 8.5
Training AUC ± SD	27	0.8070 ± 0.058	0.8050 ± 0.067	0.8310 ± 0.037
Test AUC ± SD	8	0.8068 ± 0.061	0.8052 ± 0.065	0.8307 ± 0.067

Table 3 Percentage contribution of bioclimatic variables

Variables	Current	RCP_2.6	RCP_8.5
Bio_19	36.7	21.1	38.8
Alt	26.9	36.3	29.2
Bio_12	17.5	21.5	19.4
Bio_9	9.2	4.8	1.6
Bio_2	6.6	10.5	5.3
Bio_3	2.3	3.5	4.3
Bio_11	0.8	2.3	1.4

test data in all the three scenarios, indicating good model performance (Table 2). From the Jackknife test of variable contribution, three variables contributed highest to the modelling out of 20 predictor variables, viz. (1) Precipitation of Coldest Quarter (Bio_19, 36.7%), (2) Altitude (Alt, 26.9%), and (3) Annual Precipitation (Bio_12, 17.5%), respectively under current climatic scenario (Table 3 and 4).

Analysis of the contribution of Bioclimatic variables

The individual contribution of the retained seven bioclimatic variables was obtained with the help of the Jackknife test (Table 3). In the present study, Bio_19 (Precipitation of Coldest Quarter) and altitude were the two most important variables in all three climatic scenarios that had significant influence over the distribution of the species in their native ranges (Fig. 4).

Potential distribution areas under current climatic scenario

The MaxEnt model predicted ~ 26.50% of the total geographical area of India to be climatically suitable for *B. vahlii* with very high to high probable zones primarily in the states of Himachal Pradesh and Uttarakhand in the north, parts of Jharkhand and Chhattisgarh in the east, small parts of Manipur in the north-eastern region, Andhra Pradesh, West Bengal, and Odisha in the eastern-coastal area, parts of Karnataka and Tamil Nadu in the south, Maharashtra in the west, and few regions of Madhya Pradesh in the central region (Fig. 5a). On the other hand, ~ 22.20% of the total geographical area of India was moderately suitable for *B. vahlii* with moderate probable zones in the states of Uttarakhand near its border to Uttar Pradesh, small regions of Jharkhand and Chhattisgarh in the east, significant parts of Arunachal Pradesh, small portions of Assam, and Mizoram in the north-east, parts of Andhra Pradesh, Karnataka, Telangana, and Tamil Nadu in

Table 4 Pairwise correlation coefficients between variables (Red colour indicates the variables that are correlated and excluded from the analysis)

	Alt	Bio_1	Bio_2	Bio_3	Bio_4	Bio_5	Bio_6	Bio_7	Bio_8	Bio_9	Bio_10	Bio_11	Bio_12	Bio_13	Bio_14	Bio_15	Bio_16	Bio_17	Bio_18	Bio_19
Bio_1	-0.82	1.00																		
Bio_2	-0.32	0.19	1.00																	
Bio_3	0.03	0.30	-0.35	1.00																
Bio_4	-0.15	-0.29	0.63	-0.86	1.00															
Bio_5	-0.69	0.75	0.71	-0.22	0.28	1.00														
Bio_6	-0.40	0.79	-0.30	0.74	-0.80	0.27	1.00													
Bio_7	-0.19	-0.10	0.82	-0.81	0.91	0.55	-0.65	1.00												
Bio_8	-0.96	0.76	0.44	-0.11	0.28	0.72	0.30	0.31	1.00											
Bio_9	-0.54	0.69	0.24	0.35	-0.17	0.54	0.56	-0.06	0.54	1.00										
Bio_10	-0.86	0.89	0.52	-0.11	0.16	0.94	0.44	0.36	0.86	0.63	1.00									
Bio_11	-0.52	0.89	-0.13	0.63	-0.70	0.45	0.97	-0.49	0.41	0.60	0.60	1.00								
Bio_12	0.23	-0.61	-0.08	-0.62	0.50	-0.37	-0.72	0.34	-0.24	-0.60	-0.40	-0.70	1.00							
Bio_13	0.30	-0.63	0.18	-0.71	0.64	-0.18	-0.81	0.57	-0.28	-0.48	-0.32	-0.76	0.91	1.00						
Bio_14	0.15	-0.52	-0.06	-0.35	0.42	-0.35	-0.58	0.23	-0.17	-0.31	-0.35	-0.59	0.73	0.70	1.00					
Bio_15	0.03	-0.23	0.67	-0.79	0.79	0.42	-0.66	0.91	0.05	-0.11	0.20	-0.52	0.46	0.73	0.32	1.00				
Bio_16	0.24	-0.57	0.18	-0.73	0.64	-0.14	-0.79	0.57	-0.22	-0.47	-0.27	-0.73	0.94	0.99	0.69	0.73	1.00			
Bio_17	0.38	-0.79	0.06	-0.48	0.61	-0.47	-0.84	0.36	-0.29	-0.54	-0.57	-0.89	0.70	0.74	0.70	0.38	0.69	1.00		
Bio_18	0.13	-0.58	-0.18	-0.36	0.42	-0.54	-0.61	0.10	-0.07	-0.52	-0.48	-0.67	0.77	0.60	0.68	0.08	0.59	0.80	1.00	
Bio_19	0.41	-0.47	-0.29	0.28	-0.07	-0.55	-0.15	-0.30	-0.38	-0.10	-0.58	-0.34	0.03	0.07	0.39	-0.28	-0.03	0.52	0.32	1.0
		Alt	Bio_2	Bio_3	Bio_9	Bio_11	Bio_12	Bio_19												

the south, small portions of Maharashtra in the west, and a large part of Madhya Pradesh in the central part of India.

Potential distribution of *B. vahlii* (under future climate change scenarios)

Important areas currently occupied by *B. vahlii* populations in India may lack climatic novelty in the future in both RCP 2.6 and RCP 8.5. Approximately 6.90% of India's total geographical area is climatically suitable for *B. vahlii* in RCP 2.6 as very high probable zones with an overall area expansion of 0.2% compared to the current climatic scenario. An increase of very high probable zones was observed in the areas adjacent to Himachal Pradesh and Uttarakhand in the north, Jharkhand and parts of Chhattisgarh in the east, Odisha in the eastern coastal regions, and Karnataka and Andhra Pradesh in the southern parts of India according to the potential distribution map of *B. vahlii* under RCP 2.6 (Fig. 5b). Similarly, ~ 21.5% of the total geographical area of India will be climatically suitable for *B. vahlii* as high probable zones with an overall expansion of 1.4% high probable zones compared to the current climatic scenario, mainly in the parts of eastern, eastern coastal, central, and southern India. On the other hand, ~ 26.7% of the total geographic area will be suitable for *B. vahlii* as moderate probable zones with an expansion of 4.5% compared to the current scenario, mainly in the central, upper central, southern, and north-eastern India. The model predicted ~ 45% very low to low probable zones with a decrease of ~ 6.9% in the same category compared to the current scenario, mainly lying in western states like Gujarat, Rajasthan, Punjab, and Haryana and northern states like J&K of India.

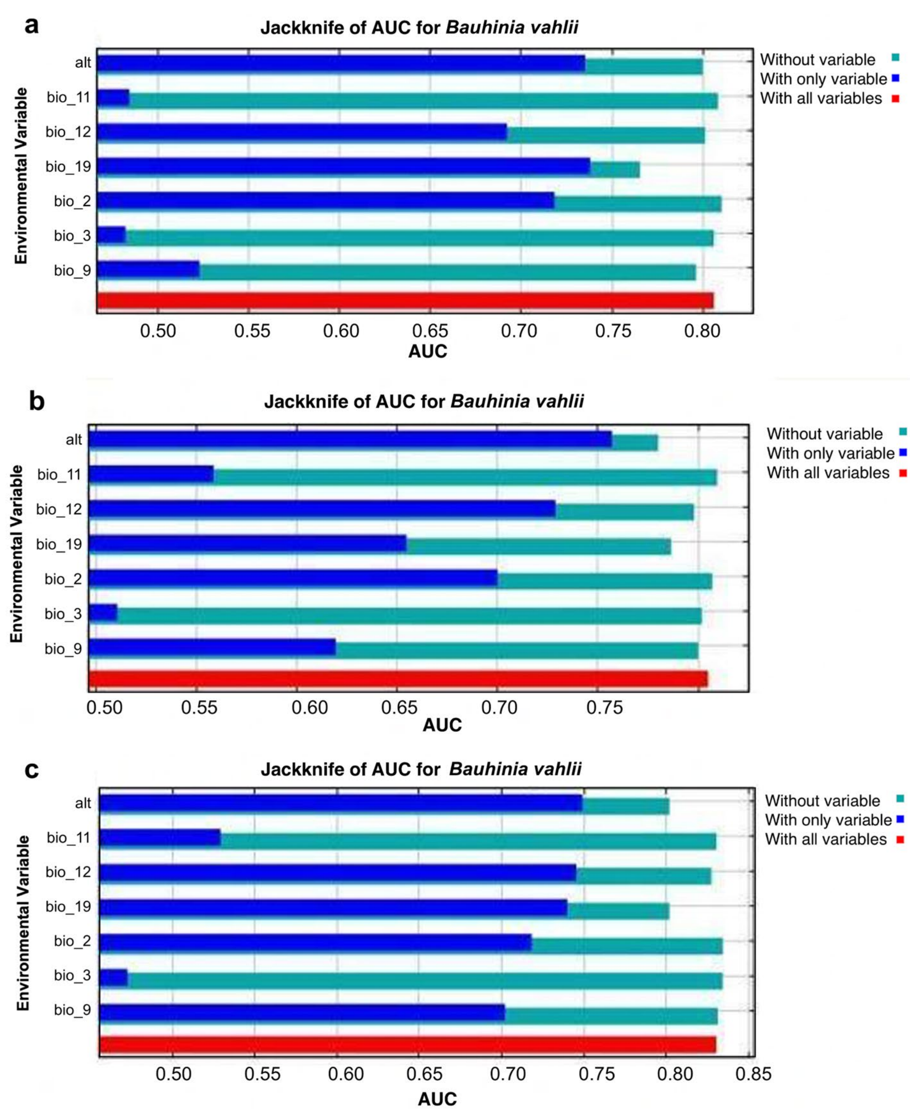

Fig. 4 Jackknife test result of AUC of *B. vahlii* in **a** Current, **b** RCP 2.6, and **c** RCP 8.5 climate change scenarios

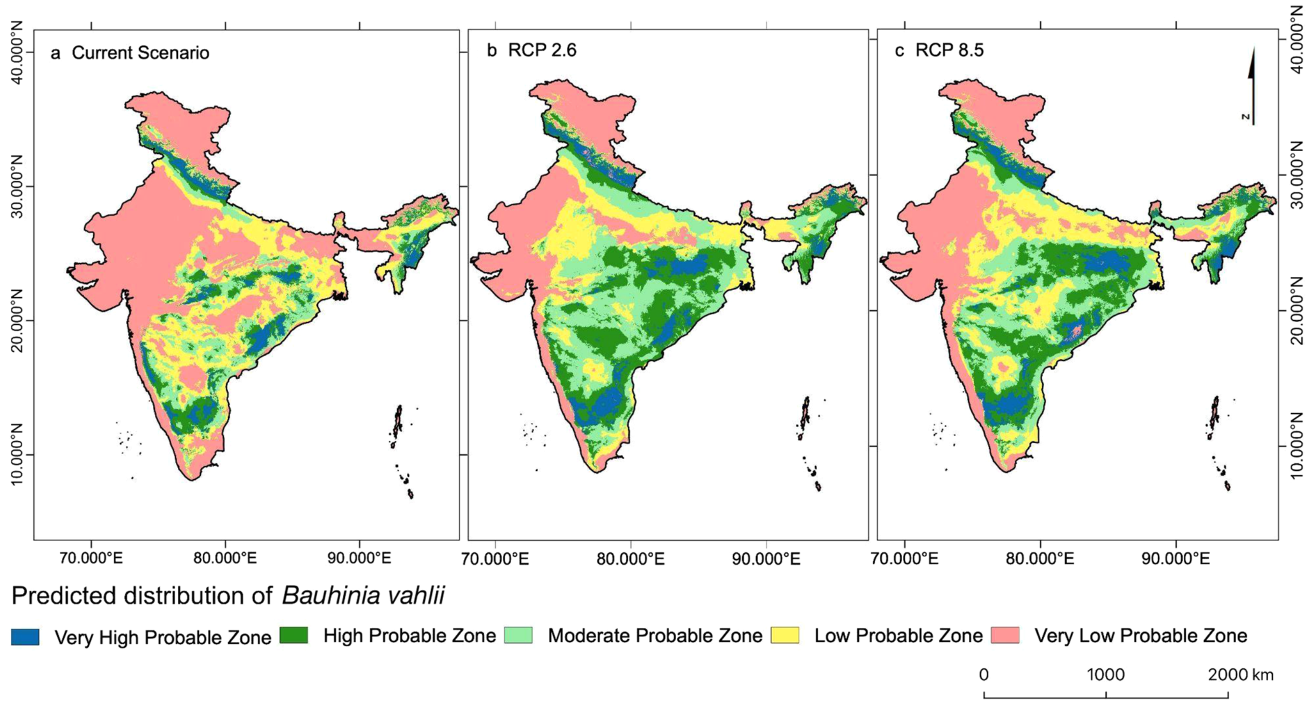

Fig. 5 Potential distribution of *B. vahlii* in **a** Current climatic scenario, **b** RCP 2.6, and **c** RCP 8.5 climate change scenarios

According to the potential distribution map of *B. vahlii* under RCP 8.5 (Fig. 5c), the model predicted a large area (~27% of the total geographical area) under very high to high probable zones with a slight expansion of ~0.5% as compared to the current scenario, which is located in Indo-Gangetic Plain, eastern, and upper southern India. In contrast, the model predicted a slight reduction in the areas, unlike RCP 2.6 in the moderate probable zones by ~0.4%, as compared to the current scenario, primarily in central and southern parts of India. Similarly, the model predicted ~51.2% area would fall under very low to low probable zones with a slight reduction of ~0.1% as compared to the current distribution mainly in the western and northern states of India like RCP 2.6 (Fig. 6).

Discussion

The natural habitat of native plant populations have been declining at an alarming rate with the influence of changing climate and the mapping of potential distribution areas of various economically important plant species through the use of predictive modelling tools can aid in the development of effective conservation management plans (Adhikari et al. 2018). The present study reported that the higher AUC value (> 0.8) symbolizes good performance of the model (Peterson et al. 2011) with better discrimination of input data (Lobo et al. 2008). Climatic variables at the global and regional scales are used to set the broad limits of plant distribution (Prentice 1992; Taylor and Hamilton 1994). In the present study, Bio_19 (Precipitation of Coldest Quarter) and altitude were the two most influential variables in all three climatic scenarios that determine the distribution of *B. vahlii* in their native ranges. On the contrary, Bio_12 (Annual Precipitation) and Bio_17 (Precipitation in the Driest Quarter) were the two most crucial bioclimatic variables contributing most towards the distribution of *Saraca asoca* having a similar current distribution range (Sumangala et al. 2017). The bioclimatic variable Bio_13 (Annual Precipitation) contributed ~30.4% to map the potentially suitable habitats of *Perilla frutescens* in Uttarakhand, India (Sharma et al. 2018). The climate of the earth has become warmer, and an alteration in the precipitation pattern has been observed in the past 100 years, and a similar alteration is projected to occur in the future, which may directly or indirectly hamper the species distribution pattern (Walther 2002). Changes in precipitation and temperature could have a deleterious effect on the regeneration of the species. Further, climate change, coupled with anthropogenic activities, could also accelerate pests, diseases, and invasive species that hamper its regeneration and establishment in the natural habitats. The effect of bioclimatic variables might be dependent on local topography, as modification in local climate occurs due to slope and other geographical factors (Lassueur et al. 2006; Austin and van Niel 2011). Therefore, to improve the distribution

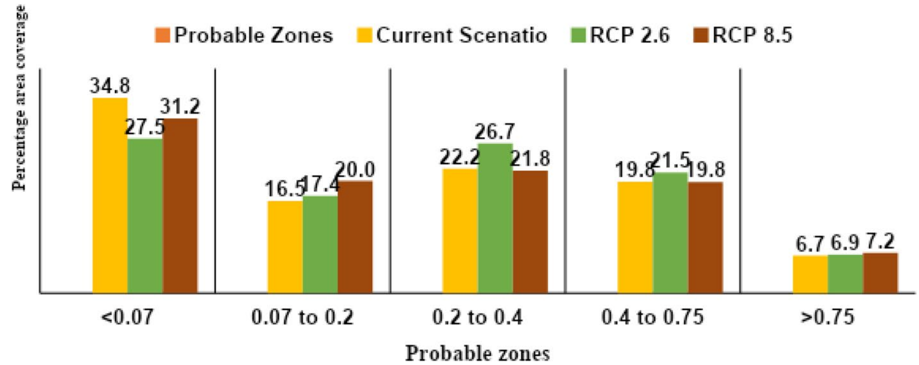

Fig. 6 Habitat suitability index of *B. vahlii* (Comparison of current, RCP 2.6, and RCP 8.5 climate change scenarios)

modelling, assessing altitude's role becomes significant as it is one of the prime contributing factors in the present study.

Habitat loss, deforestation, forest degradation, over-exploitation, changing climate, and land degradation are major threats faced by a range of native Indian species (Rajpoot et al. 2020). *Bauhinia vahlii* is also facing a range of ecological disturbances including the over-exploitation for medicinal purposes, small-scale plate making industries, grazing by the livestock, herbivory by insect pests, etc. (Nadkarni 2005; Mishra and Teki 2007; Kandhasamy and Kang 2013). Different authors report climate suitability in the regions adjacent to Himachal Pradesh and Uttarakhand in the north, Jharkhand and parts of Chhattisgarh in the east, Odisha in the eastern coastal regions, and Karnataka and Andhra Pradesh in the southern parts of India for various other plant species too (Sen et al. 2016a; Ray et al. 2018; Sharma et al. 2018; Bhandari et al. 2020). However, the above-stated regions pose high suitability for invasive alien species, posing an additional threat to species survival (Adhikari et al. 2015). The model predicted ~ 51.3% of the total geographic area as very low to low probable zones falling mainly in the western states like Rajasthan, Gujarat, Punjab, Haryana, and extreme northern states like J&K of India. Comparing the current distribution with future distributions would help in understanding species' response to climate change, and ultimately helps in formulating effective conservation strategies (Warren et al. 2013; Russel et al. 2014).

The moderate expansion of distribution area under both the climate change scenarios, *i.e.* RCP 2.6 and RCP 8.5, as compared to the predicted optimal current distribution range, was also reported in *Thuja sutchuenensis* in China (Qin et al. 2017). On the other hand, there was a shrinkage of climatically suitable areas of *Boswellia serrata* (~ 7 to 14%) (Rajpoot et al. 2020), *Butea monosperma* (~ 9–13%) and also in *Pterocarpus marsupium* (Kumar et al. 2020) in 2050 under various RCPs (Tiwari et al. 2021). It is evident that climate change might favor some species and might have negative impacts on others. There are high chances of increase in moderately suitable areas of invasive weeds like *Parthenium hysterophorus* in Jammu & Kashmir under different RCPs in 2050 and 2070 (Mushtaq et al. 2021). Such model-based studies may play an important role in formulating strategies to protect the rare and endangered species and help in planning management protocols for invasive species.

The present study was the first attempt to explore the impact of climate change on the distribution pattern of *B. vahlii* across the study area using the MaxEnt algorithm. MaxEnt has been widely used to determine the species suitable habitat because it performs well with a limited number of presence only data sets (Phillips et al. 2006; Elith et al. 2006). Our findings suggested that, potential suitable habitat of *B. vahlii* would expand under future climatic change scenarios (RCP 2.6 and RCP 8.5) indicating more suitable habitats would be available for the artificial cultivation of *B. vahlii* in future. The potential suitable habitat map of *B. vahlii* under current and future climatic change scenarios can be one of the guiding tools for the decision makers to set effective strategies for its conservation and sustainable utilization.

Model limitations and uncertainties

Inappropriate selection of predictive variables for MaxEnt modeling might become the source of uncertainties, because there might exist overfitting results (Radosavljevic et al. 2014; Wei et al. 2018). In the present study, the potential distribution of *B. vahlii* is predicted based on the bioclimatic and topographic variables like altitude, mean diurnal range (Bio_2), isothermality (Bio_3), mean temperature of driest quarter (Bio_9), mean temperature of coldest quarter (Bio_11), annual precipitation (Bio_12), and precipitation of coldest quarter (Bio_19). The influence of non-climatic factors such as changes in land uses, soil type, and biotic interactions could be considered in future research to further improve the model outputs. Secondly, species occurrence records are spatially biased towards more easily accessible areas such as near roads, cities, and highly populated areas. These sampling biases artificially increase spatial autocorrelation of the localities and affect the model accuracy

(Phillips et al. 2009; Ruiz-Gutierrez and Zipkin 2011; Boria et al. 2014). When these limitations are properly addressed, then MaxEnt can remain as one of the powerful tool in prediction of potential distribution of species.

Conclusions

It is predicted that *B. vahlii* will respond variably under different climate change scenarios. The predicted impacts of climate change need to be integrated for conservation and management of this economically important, multipurpose woody climber. There is an urgent need to focus on the management strategies of *B. vahlii* populations found in southern, Central, and Northeastern parts, where suitable habitat is likely to shrink under future climatic scenarios and the concern lies in monitoring the direction of the niche shift, otherwise populations might decline or disappear under climate change in these regions. Focus is also required primarily towards the eastern and south-eastern parts of India based on the species' response to the variations in bioclimatic variables, where the habitat is likely to gain suitable area under future climatic conditions. The present study can help and assist in effective policy formulation to safeguard *B. vahlii* as it is highly exploited and more vulnerable to climate change impacts throughout its distributional range mainly in Gumla and Latehar districts of Jharkhand due to its multipurpose uses like its leaves are used in the plate making industries and root extracts in medicinal purposes. In conclusion, the prediction from ecological niche models along with other data including demographic data, land cover data, and anthropogenic pressures could serve as a useful tool to identify suitable areas for the conservation of the species. Hence, there is an urgent need for strict policy interventions to check its overexploitation, monitor the niche shift, and ensure adequate protection of the species throughout its distributional range.

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Author contributions KKT participated in the field data collection, analyses, and interpretation, and drafted the manuscript; PB analyzed, and interpreted data and drafted the manuscript; AK helped in analyses and preparation of maps and also in finalizing the manuscript; PS & GR conceived the study, and also finalized the manuscript. All authors read and approved the final manuscript.

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Declarations

Conflict of interest The authors declare that they have no competing interests.

Ethics approval, consent to participate, and consent for publication Not applicable.

References

Adhikari D, Tiwary R, Barik SK (2015) Modelling hotspots for invasive alien plants in India. PLoS ONE 10:e0134665

Adhikari D, Reshi Z, Datta BK, Samant SS, Chettri A, Upadhaya K, Shah MA, Singh PP, Tiwary R, Majumdar K, Pradhan A, Thakur ML, Salam N, Zahoor Z, Mir MH, Kaloo ZA, Barik SK (2018) Inventory and characterization of new populations through ecological niche modelling improve threat assessment. Curr Sci 114:519–531

Aiello-Lammens ME, Boria RA, Radosavljevic A, Vilela B, Anderson RP (2015) spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. Ecography 38:541–545

Andrewartha HG, Birch LC (1954) The distribution and abundance of animals. University of Chicago Press, Chicago

Austin MP, van Niel KP (2011) Improving species distribution models for climate change studies: variable selection and scale. J Biogeogr 38:1–8

Bagchi B, Banerjee D (2013) Diversity of fungal endophytes in *Bauhinia vahlii* (a liana) from different regions of Paschim Medinipur district of West Bengal. IJSET 2:748–756

Becerra Lopez JL, Esparza Estrada CE, Romero Mendez U, Sigala Rodriguez JJ, Mayer Goyenechea IG, Castillo Ceron JM (2017) Evidence of niche shift and invasion potential of *Lithobates catesbeianus* in the habitat of Mexican endemic frogs. PLoS ONE 12:e0185086

Bellard C, Bertelsmeier C, Leadley P, Thuiller W, Courchamp F (2012) Impacts of climate change on the future of biodiversity. Ecol Lett 15:365–377

Bhandari MS, Meena RK, Shankhwar R, Shekhar C, Saxena J, Kant R, Pandey VV, Barthwal S, Pandey S, Chandra G, Ginwa HS (2020) Prediction mapping through maxent modeling paves the way for the conservation of *Rhododendron arboreum* in Uttarakhand Himalayas. J Indian Soc Remote Sens 48:411–422

Bisby F (1994) Phytochemical dictionary of the leguminosae. CRC Press

Busby JR (1991) BIOCLIM- a bioclimate analysis and prediction system. Plant Prot Q 6:8–9

Chen IC, Shiu HJ, Benedick S, Holloway JD, Chey VK, Barlow HS, Jane KH, Chris DT (2009) Elevation increases in moth assemblages over 42 years on a tropical mountain. Proc Natl Acad Sci USA 106:1479–1483

Das SN, Jagannath PV, Dinda SC (2012) Evaluation of Anti-Inflammatory, Antidiabetic activity of Indian *Bauhinia vahlii* (stembark). Asian Pac J Trop Biomed 2:S1382–S1387

de Siqueira MF, Durigan G, de Marco JP, Peterson AT (2009) Something from nothing: using landscape similarity and ecological niche modeling to find rare plant species. J Nat Conserv 7:25–32

Dhar U, Upreti J (1999) In vitro regeneration of a mature leguminous liana (*Bauhinia vahlii* Wight & Arnott). Plant Cell Rep 18:664–669

Dormann CF, Elith J, Bacher S, Buchmann C, Carl G (2013) Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36:27–46

Dugasani S, Balijepalli MK, Tandra S, Pichika MR (2010) Antimicrobial activity of *Bauhinia tomentosa* and *Bauhinia vahlii* roots. Pharmacogn Mag 6:204–207

Elith J, Graham CH, Anderson RP, Dudik M, Ferrier S, Guisan A, Hijmans RJ, Huettmann F, Leathwick JR, Lehmann A, Li J, Lohmann LG, Loiselle BA, Manion G, Moritz C, Nakamura M, Nakazawa Y, McC OJ, Peterson AT, Phillips SJ, Richardson KS, Scachetti-Pereira R, Schapire RE, Sobero NJ, Williams S, Wisz MS, Zimmermann NE (2006) Novel methods improve prediction of species' distributions from occurrence data. Ecography 29:129–151

Elith J, Kearney M, Phillips S (2010) The art of modelling range-shifting species. Methods Ecol Evol 1:330–342

Elith J, Phillips SJ, Hastie T, Dudik M, Chee YE, Yates CJ (2011) A statistical explanation of MaxEnt for ecologists. Divers Distrib 17:43–57

Feeley KJ, Malhi Y, Zelazowski P, Silman MR (2012) The relative importance of deforestation, precipitation change, and temperature sensitivity in determining the future distributions and diversity of Amazonian plant species. Glob Chang Biol 18:2636–2647

Franklin J (2010) Mapping species distributions: spatial inference and prediction. Cambridge University Press, Cambridge

Friedman J, Hastie T, Tibshirani R (2000) Additive logistic regression: a statistical view of boosting. Ann Stat 28:337–407

Ganeshaiah KN, Barve N, Nath N, Chandrashekara K, Swamy M, Shaanker RU (2003) Predicting the potential geographical distribution of the sugarcane woolly aphid using GARP and DIVA-GIS. Curr Sci 85:1526–1528

GBIF (2020) GBIF.org (04 February 2020) GBIF Occurrence Download https://doi.org/10.15468/dl.uxsyn3

Gelfand AE, Silander JA Jr, Wu S, Latimer A, Lewis PO, Rebelo AG, Holder M (2006) Explaining species distribution patterns through hierarchical modeling. Bayesian Anal 1:41–92

Graham CH, Ferrier S, Huettman F, Moritz C, Peterson AT (2004) New developments in museum-based informatics and applications in biodiversity analysis. Trends Ecol Evol 19:497–503

Grinnell J (1917) Field tests of theories concerning distributional control. Am Nat 51:115–128

Grinnell J (1924) Geography and evolution. Ecology 5:225–229

Guisan A, Tingley R, Baumgartner JB, Naujokaitis-Lewis I, Sutcliffe PR, Tulloch AI, Regan TJ, Brotons L, McDonald-Madden E, Mantyka-Pringle C, Martin TG, Rhodes JR, Maggini R, Setterfield SA, Elith J, Schwartz MW, Wintle BA, Broennimann O, Austin M, Ferrier S, Kearney MR, Possingham HP, Buckley YM (2013) Predicting species distributions for conservation decisions. Ecol Lett 16:1424–1435

Gupta BN (2005) Mahul Patta: NTFP-India: production availability, prices. ICRF Tech. Series Publication, Dehradun, India

Hamid M, Khuroo AA, Charles B, Ahmad R, Singh CP, Aravind NA (2019) Impact of climate change on the distribution range and niche dynamics of Himalayan birch, a typical treeline species in Himalayas. Biodivers Conserv 28:2345–2370

Hijmans RJ (2012) Cross-validation of species distribution models: removing spatial sorting bias and calibration with a null model. Ecology 93:679–688

Hijmans RJ, Garrett KA, Huaman Z, Zhang DP, Schreuder M, Bonierbale M (2000) Assessing the geographic representativeness of genebank collections: the case of Bolivian wild potatoes. Conserv Biol 14:1755–1765

Hijmans RJ, Guarino L, Cruz M, Rojas E (2001) Computer tools for spatial analysis of plant genetic resources data: 1. DIVA-GIS Plant Genet Resour Newsl 127:15–19

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A (2005) Very high-resolution interpolated climate surfaces for global land areas. Int J Climatol 25:1965–1978

Hill DS (1987) Agricultural insect pests of temperate regions and their control. Cambridge University Press, Cambridge

Hutchinson GE (1957) Concluding remarks. Cold Spring Harb Symp Quant Biol 22:415–442

IPCC Climate change (2013) the physical science basis. In: Stocker TF, Qin D, Plattner GK,Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM (ed) Contribution of working group I to the fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, New York, pp1535

IPCC Climate Change (2014) Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In: Pachauri RK, Meyer LA (ed) IPCC, Geneva, Switzerland, pp151

Joshi M, Charles B, Ravikanth G, Aravind NA (2017) Assigning conservation value and identifying hotspots of endemic rattan diversity in the Western Ghats, India. Plant Divers 39:263–272

Kadmon R, Farber O, Danin A (2004) Effect of roadside bias on the accuracy of predictive maps produced by bioclimatic models. Ecol Appl 14:401–413

Kandhasamy S, Kang SC (2013) Free radical scavenging activity from different extracts of leaves of *Bauhinia vahlii* Wight & Arn. Saudi J Biol Sci 20:319–325

Kandi B, Sahu SC, Dhal NK, Mohanty RC (2011) Species diversity of vascular plants of Sunabeda wildlife sanctuary, Odisha, India. N Y Sci J 4:1–9

Kumar R, Saikia P (2020) Forests resources of Jharkhand, Eastern India: Socio-economic and bioecological perspectives. In: Roy N, Roychoudhury S, Nautiyal S, Agarwal SK, Baksi S (eds) Socio-economic and Eco-Biological Dimensions in Resource use and Conservation - Strategies for Sustainability. Springer International Publishing, Switzerland, pp 61–101

Kumar A, Kumar A, Adhikari D, Ravikanth G, Saikia P, Khan ML (2020) Ecological niche modelling for assessing potential distribution of *Pterocarpus marsupium* Roxb. In Ranchi, Eastern India. Ecol Res 35:1095–1105

Lal P, Kumar A, Saikia P, Das A, Patnaik C, Kumar G, Pandey AC, Srivastava P, Dwivedi CS, Khan ML (2021) Effect of Vegetation Structure on Above Ground Biomass in Tropical Deciduous Forests of Central India. Geocarto Int 1–5

Lassueur T, Joost S, Randin CF (2006) Very high-resolution digital elevation models: do they improve models of plant species distribution? Ecol Modell 198:139–153

Lehmann A, Overton JM, Leathwick JR (2002) GRASP: generalized regression analysis and spatial prediction. Ecol Modell 157:189–207

Loarie SR, Carter BE, Hayhoe K, McMahon S, Moe R, Knight CA, Ackerly DD (2008) Climate change and the future of California's endemic flora. PLoS ONE 3:e2502

Lobo JM, Jimenez-Valverde A, Real R (2008) AUC: misleading measure of the performance of predictive distribution models. Glob Ecol Biogeogr 17:145–151

Manandhar NP (2002) Plants and People of Nepal. Timber Press, Oregon

Mastan T, Parveen SN, Reddy MS (2015) Liana species inventory in a tropical dry forest of Sri Lankamalla Wildlife Sanctuary, Andhra Pradesh, India. J Environ Dev 9:1024–1030

Merow C, Smith MJ, Silander JA Jr (2013) A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36:1058–1069

Mishra S, Chaudhury SS (2012) Ethnobotanical flora used by four major tribes of Koraput, Odisha, India. Genet Resour Crop Evol 59:793–804

Mishra M, Teki S (2007) Present harvesting practices of Siali leaves (*Bauhinia vahlii*) and its impact on plant density and regeneration in the natural forest of three districts of Odisha. J Trop For 23:77–86

Moss RH, Edmonds JA, Hibbard KA, Manning MR, Rose SK, van Vuuren DP, Carter TR, Emori S, Kainuma M, Kram T, Meehl GA, Mitchell JF, Nakicenovic N, Riahi K, Smith SJ, Stouffer RJ, Thomson AM, Weyant JP, Wilbanks TJ (2010) The next generation of scenarios for climate change research and assessment. Nature 463:747–756

Murray KA, Retallick RW, Puschendorf R, Skerratt LF, Rosauer D, McCallum HI, Berger L, Speare R, Van Der Wal J (2011) Assessing spatial patterns of disease risk to biodiversity: implications for the management of the amphibian pathogen, *Batrachochytrium dendrobatidis*. J Appl Ecol 48:163–173

Mushtaq S, Reshi ZA, Shah MA, Charles B (2021) Modelled distribution of an invasive alien plant species differs at different spatiotemporal scales under changing climate: a case study of *Parthenium hysterophorus* L. Trop Ecol 62:398–417

Nadkarni AK (1954) Indian Materia Medica, 3rd edn. Popular Prakashan Private Ltd., Bombay

Nadkarni AK, Nadkarni KM (2005) Indian Materia Medica. Popular Prakashan Private Ltd., Mumbai

Nagaraju SK, Ravikanth G, Narayani B, Jaboury G, Ganeshaiah KN, Shaanker RU (2013) Do ecological niche model predictions reflect the adaptive landscape of species? A test using *Myristica malabarica* Lam., an endemic tree in the Western Ghats, India. PLoS ONE 8:e82066

O'Donnell MS, Ignizio DA (2012) Bioclimatic predictors for supporting ecological applications in the conterminous United States: US Geol Surv Data Ser 691:10

Parmesan C, Yohe G (2003) A globally coherent fingerprint of climate change impacts across natural systems. Nature 421:37–42

Parrotta JA (2001) Healing plants of Peninsular India. CABI Publishing, New York

Patole SN, Jain AK (2002) Some edible plants of Pachmarhi Biosphere Reserve (MP). Ethnobotany 14:48–51

Pattanaik C, Reddy CS, Das R, Reddy PM (2007) Traditional medicinal practices among the tribal people of Malkangiri district, Orissa, India. Nat Prod Rad 6:430–435

Pearce J, Ferrier S (2000) Evaluating the predictive performance of habitat models developed using logistic regression. Ecol Model 133:225–245

Pearson RG, Raxworthy CJ, Nakamura M, Townsend Peterson A (2007) Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. J Biogeogr 34:102–117

Peh KS (2007) Potential effects of climate change of elevational distributions of tropical birds in Southeast Asia. Condor 109:437–441

Peterson AT (2003) Predicting the geography of species' invasions via ecological niche modeling. Q Rev Biol 78:419–433

Peterson AT (2006) Ecological niche modeling and spatial patterns of disease transmission. Emerg Infect Dis 12:1822–1826

Peterson AT, Soberon J, Pearson RG, Anderson RP, Martinez-Meyer E, Nakamura M, Araujo MB (2011) Ecological niches and geographic distributions. Princeton University Press, Princeton

Phillips SJ, Dudik M (2008) Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31:161–175

Phillips SJ, Anderson RP, Schapire RE (2006) Maximum entropy modeling of species geographic distributions. Ecol Modell 190:231–259

Phillips SJ, Dudik M, Elith J, Graham CH, Lehmann A, Leathwick J, Ferrier S (2009) Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. Ecol Appl 19:181–197

Phillips SJ (2017) A Brief Tutorial on Maxent. http://biodiversityinformatics.amnh.org/open_source/maxent/

Polak T, Saltz D (2011) Reintroduction as an ecosystem restoration technique. Conserv Biol 25:424–427

Prasad P, Nautiyal AR (2003) Effect of orientation of seed placement in soil on seedling emergence in two *Bauhinia* species: *Bauhinia vahlii* Wight & Arn. and *Bauhinia racemosa* Lam. Seed Sci Technol 31:497–503

Priti H, Aravind NA, Shaanker RU, Ravikanth G (2016) Modeling impacts of future climate on the distribution of Myristicaceae species in the Western Ghats, India. Ecol Eng 89:14–23

Qin A, Liu B, Guo Q, Bussmann RW, Ma F, Jian Z, Xu G, Pei S (2017) Maxent modeling for predicting impacts of climate change on the potential distribution of *Thuja sutchuenensis* French., An extremely endangered conifer from southwestern China. Glob Ecol Conserv 10:139–146

Rajaram N, Janardhanan K (1991) Chemical composition and nutritional potential of the tribal pulses *Bauhinia purpurea, B. racemosa,* and *B. vahlii*. J Sci Food Agric 55:423–431

Rajesh K, Singh Manish K, Avinash BK (2013) Ethnobotany of Tharus of Dudhwa national park, India. Mintage J Pharm Med Sci 2:6–11

Rajpoot R, Adhikari D, Verma S, Saikia P, Kumar A, Grant KR, Dayanandan A, Kumar A, Khare PK, Khan ML (2020) Climate models predict a divergent future for the medicinal tree *Boswellia serrata* Roxb. in India. Glob Ecol Conserv 23:e01040

Ray D, Behera MD, Jacob J (2018) Evaluating ecological niche models: a comparison between Maxent and GARP for predicting distribution of *Hevea brasiliensis* in India. Proc Natl Acad Sci India Sect B Biol Sci 88:1337–1343

Reddy S, Davalos LM (2003) Geographical sampling bias and its implications for conservation priorities in Africa. J Biogeogr 30:1719–1727

Reddy CS, Ugle P (2008) Tree species diversity and distribution patterns in tropical forest of Eastern Ghats, India: a case study. Life Sci J 5:87–93

Retana J, Rodriguez N, Armenteras D (2009) Are conservation strategies effective in avoiding the deforestation of the Colombian Guyana Shield? Biol Conserv 142:1411–1419

Roskov Y, Zarucchi J, Novoselova M, Bisby F (eds) (2019) ILDIS World Database of Legumes (version 12, May 2014). In: Species 2000 & ITIS Catalogue of Life, 2019 Annual Checklist

Russell J, Van Zonneveld M, Dawson IK, Booth A, Waugh R, Steffenson B (2014) Genetic diversity and ecological niche modelling of wild barley: refugia, large-scale post-LGM range expansion, and limited mid-future climate threats? PLoS ONE 9:e86021

Samant SS, Dhar U, Rawal RS (2000) Assessment of fuel resource diversity and utilization patterns in Askot Wildlife Sanctuary in Kumaun Himalaya, India, for conservation and management. Environ Conserv 27:5–13

Samant SS, Dhar U, Rawal RS (2006) Diversity, extraction, and status of fodder species in Askot Wildlife Sanctuary, West Himalaya, India. Int J Biodivers Sci Manag 2:29–42

Sankara RK, Raja KS, Kumar D, Singh AR, Bhat KG (2019) Flora of Peninsular India. http://peninsula.ces.iisc.ac.in/plants.php?name=Bauhiniavahlii

Seimon TA, Seimon A, Daszak P, Halloy SR, Schloegel LM, Aguilar CA, Sowell P, Hyatt AD, Konecky B, Simmons EJ (2007) Upward range extension of Andean anurans and chytridiomycosis to extreme elevations in response to tropical deglaciation. Glob Chang Biol 13:288–299

Sen S, Ameya G, Srirama R, Ravikanth G, Aravind NA (2016a) Modeling the impact of climate change on wild *Piper nigrum* (Black Pepper) in Western Ghats, India using Ecological Niche models. J Plant Res 129:1033–1040

Sen S, Shivaprakash KN, Aravind NA, Ravikanth G, Dayanandan S (2016b) Ecological niche modeling for conservation planning of an endemic snail in the verge of becoming a pest in cardamom plantations in the Western Ghats Biodiversity Hotspot. Ecol Evol 6:6510–6523

Sharma S, Arunachalam K, Bhavsar D, Kala R (2018) Modeling habitat suitability of *Perilla frutescens* with MaxEnt in Uttarakhand-A conservation approach. J Appl Res Med Aromat Plants 10:99–105

Shrestha UB, Sharma KP, Devkota A, Siwakoti M, Shrestha BB (2018) Potential impact of climate change on the distribution of six invasive alien plants in Nepal. Ecol Ind 95:99–107

Singh H, Kumar N, Kumar M, Singh R (2020) Modelling habitat suitability of western tragopan (*Tragopan melanocephalus*) a range-restricted vulnerable bird species of the Himalayan region, in response to climate change. Clim Risk Manag 29:100241

Soberon J, Peterson AT (2005) Interpretation of models of fundamental ecological niches and species' distributional areas. Biodivers Inform 2:1–10

Sowndhararajan K, Kang SC (2013) Free radical scavenging activity from different extracts of leaves of *Bauhinia vahlii* Wight & Arn. Saudi J Biol Sci 20:319–325

Sowndhararajan K, Siddhuraju P, Manian S (2010) In vitro evaluation of the antioxidant activities in the differentially processed seeds from underutilized legume, *Bauhinia vahlii* Wight & Arn. Food Sci Biotechnol 19:503–509

Steven J, Phillips SJ (2009) A brief tutorial on Maxent. Network of conservation educators and practitioners. Center for Biodiversity and Conservation, American Museum of Natural History. Lessons Conserv 3:108–135

Stevnbak K, Scherber C, Gladbach D, Christensen S (2009) Climate change strongly affects interaction between herbivorous insects, plants, and rhizosphere biota. Earth Environ Sci 6:042104

Stockwell D (1999) The GARP modelling system: problems and solutions to automated spatial prediction. Int J Geogr Inf Sci 13:143–158

Subba B, Sen S, Ravikanth G, Nobis MP (2018) Direct modelling of limited migration improves projected distributions of Himalayan amphibians under climate change. Biol Conser 227:352–360

Sumangala RC, Rosario S, Charles B, Ganesh D, Ravikanth G (2017) Identifying Conservation priority sites for *Saraca asoca*: an important medicinal plant using ecological Niche models. Indian For 143:531–536

Sutherst RW, Maywald GF, Skarratt DB (1995) Predicting insect distributions in a changed climate. In: Harrington R, Stork NE (eds) Insects in a changing environment. Academic Press, London, pp 59–91

Thapa S, Chitale V, Rijal SJ, Bisht N, Shrestha BB (2018) Understanding the dynamics in distribution of invasive alien plant species under predicted climate change in Western Himalaya. PLoS ONE 13:e0195752

Thomas CD, Cameron A, Green RE, Bakkenes M, Beaumont LJ, Collingham YC, Erasmus BF, De Siqueira MF, Grainger A, Hannah L, Hughes L, Huntley B, van Jaarsveld AS, Midgley GF, Miles L, Ortega-Huerta MA, Peterson AT, Phillips OL, Williams SE (2004) Extinction risk from climate change. Nature 427:145–148

Thuiller W, Lafourcade B, Engler R, Araujo MB (2009) BIOMOD–a platform for ensemble forecasting of species distributions. Ecography 32:369–373

Tiwari S, Ghosh BG, Vaidya SN, Rahaman SK, Khatun M, Garai S, Saikia P, Kumar A (2021) Modelling potentially suitable lac cultivation zones of *Butea monosperma* to promote livelihood security in rural India. Vegetos 34:630–637

Tiwari GP, Tadele K, Aramde F, Tiwari SC (2010) Community structure and regeneration potential of *Shorea robusta* forest in subtropical submontane zone of Garhwal Himalaya, India. Nat Sci:70–74

Upreti J, Dhar U (1996) Micropropagation of *Bauhinia vahlii* Wight & Arn.—a leguminous liana. Plant Cell Rep 16:250–254

Urban MC (2015) Accelerating extinction risk from climate change. Science 348:571–573

Vadivel V, Janardhanan K (2000) Effect of post-harvest treatments on nutritional attributes of the tribal pulse, *Bauhinia vahlii* W. and A. Swamy. Bot Cl 17:57–59

Walther GR, Post E, Convey P, Menzel A, Parmesan C, Beebee TJ, Fromentin JM, Hoegh-Guldberg O, Bairlein F (2002) Ecological responses to recent climate change. Nature 416:389–395

Warren R, VanDerWal J, Price J, Welbergen JA, Atkinson I, Ramirez-Villegas J, Osborn TJ, Jarvis A, Shoo LP, Williams SE, Lowe J (2013) Quantifying the benefit of early climate change mitigation in avoiding biodiversity loss. Nat Clim Change 3:678–682

Wisz MS, Hijmans RJ, Li J, Peterson AT, Graham CH, Guisan A (2008) Effects of sample size on the performance of species distribution models. Divers Distrib 14:763–773

Yee TW, Mitchell ND (1991) Generalized additive models in plant ecology. J Veg Sci 2:587–602