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Predicting the habitat suitability of *Dipterocarpus indicus*: an endemic and endangered species in the Western Ghats, India

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Abstract Species distribution models provide habitat mapping tools and produce scalable information to inform policy decisions. Integrating spatial statistical modelling with bioclimatic information identifies the contribution of the most critical variable in species occurrence and distribution. In the present study a suitable bioclimatic model, MaxEnt modelling algorithm is used for *Dipterocarpus indicus*, an endemic and endangered species by incorporating field inventory data.This model predicted a high probability of potential distribution area in the forests of Uttara Kannada, Chikmagalur, Shivamogga and Kannur. The highly suitable hábitats are distributed in protected áreas, namely Kudremukh, Mookambika, Pushpagiri, Sharavathi Valley, Shettihalli, Someshwara, Parambikulam, Peechi-Vazhani, Shendurney, Thattekadu Bird, Indira Gandhi (Anamalai), Kalakad, Mundanthurai and Kanyakumari. The Area Under Curve value for the potential distribution of species is observed at 0.894 for training data. The highest fractional predicted area was in the low elevation tropical wet evergreen forest region between 50 and 700 m. The contributions of the climatic variables in the model showed that precipitation in the coldest quarter was the most influential, followed by annual mean temperature and annual precipitation. This study aids in long-term conservation planning, monitoring, and managing potential habitats of endemic and endangered tree species.

Keywords Endemic Endangered · Climate · Biodiversity hotspot · SDM · MaxEnt · Remote sensing

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1 Introduction

The role of remote sensing data in biodiversity monitoring was documented in Aichi biodiversity targets and essential biodiversity variables. Biodiversity conservation requires spatial data on the distribution of endemic and threatened species, biologically significant areas, and protected areas. Understanding the relationships between species and their abiotic and biotic environment is essential to conserve species. The influencing factor between species distribution and selection of habitat are decisive to researchers because the distribution of rare species is challenging to monitor and protect when their habitat preferences are not known clearly [1, 2]. Such research problems can be addressed using species distribution models (SDMs) or habitat suitability models, using environmental and geographic information explaining the observed patterns of species occurrences and providing information on exploring the species and predicting the species distributions across the different landscapes [3, 4]. Species Distribution Models (SDMs) estimate the potential distributional range by combining the information on the geographic occurrence of species adding with environmental layers. SDMs are beneficial for ecologists concerning inventory, conservation, and restoration ecology.

The predicted species distribution models help measure habitat suitability [4]. This information can help recognize habitats and unidentified populations of endemic, rare or threatened species and invasive species [5–7]. The most acceptable and broadly used model in recent times is Maxent Model [8]. Maxent algorithm predicts the suitable habitat based on climatic or remotely sensed variables and species occurrence. Maxent even executes well with small sample sizes [9]. The model can be assessed with the ground data to observe the prediction or habitat suitability [10].

Species Distribution Modelling has been carried out on various endemic and endangered plant species. One of the examples is *Pterocarpus santalinus* L.f. confined to the southern portion of Eastern Ghats in Andhra Pradesh, India [11]. Furthermore, the study was conducted by [12] on *Spiranthes parksii*, a state-listed endangered terrestrial orchid endemic to central Texas. In addition, habitat modelling for reintroducing endangered medicinal plants—*Ephedra gerardiana, Lilium polyphyllum, Crepidium acuminatum, Pittosporum eriocarpum* and *Skimmia anquetilia* was conducted in India [13].

Evaluating endemic plant species distribution is critical to determine their status and improve conservation management efforts [14, 15]. The species distribution model (SDMs) in the study addresses this issue. This statistical algorithm has a strong predictive ability by analysing the species-environmental relationships in space and time by extrapolating the information from incomplete data.

The study by [16] reported a forest cover loss of 35.3% from 1920 to 2013, indicating the Western Ghats represent vulnerable ecosystems. Species occurrence data and spatial bioclimatic variables are used in this study, aiming to identify the ecologically suitable zones of *Dipterocarpus indicus* and determine whether the results of species modelling were executed with the help of remote sensing. Machine learning algorithms are comparable at the landscape level. The *Dipterocarpus indicus* dominates the international tropical timber market because of its high wood quality for making plywood. Wood is reddish-brown, hard, and used for house construction, shipbuilding, and railway carriages. In addition, the oleoresin is employed to prepare lithographic inks, spirit, and oil varnishes and treat rheumatic complaints. Endemic to the Western Ghats in South-West India, the current threat status of *Dipterocarpus indicus* is endangered at the global level [17, 18].

2 Material and methods

2.1 Study area

The Western Ghats of India extending from the latitudinal degree of 8° N to 22° N down 1500 km in length from the Tapti River in the north to Kanyakumari in the south. It covers parts of six states, viz. Gujarat, Maharashtra, Karnataka, Goa, Kerala, Tamil Nadu and a union territory (Dadra and Nagar Haveli). Among India's hotspots, the Western Ghats account for 64.95%, Indo-Burma for 5.13%, Himalaya for 44.37% and Sundaland for 1.28% of area. The Western Ghats is one of the Hotspots of biological diversity in the Old-World tropics [16]. The spatial boundary generated from India's revised biogeographic zone map [19] has a geographical area of about 130,500 km^2 (Fig. 1). The study by [20] reported a moderate level of forest fragmentation in the Western Ghats.

2.2 Data used for modelling species distribution

The geographical coordinates for each locality for *Dipterocarpus indicus* Bedd. were collected from the database of biodiversity characterisation at landscape level project [21] and national carbon project [22]. A total of 52 locations of *Dipterocarpus indicus* were collected randomly in the Western Ghats using Global Positioning System (GPS). The low elevation wet evergreen forest (*Dipterocarpus indicus–Diospyros candolleana–Diospyros oocarpa* type) is shown in Fig. 2. In addition, vegetation type-maps, high-resolution data from Bhuvan [23], Google Earth data [24], protected areas, the biogeographic zones [25], and climate data [26] are used in the generation of locality attributes. The Shuttle Radar Topography Mission (SRTM) with 90 m spatial resolution is used to generate the aspect, slope and elevation data [27].

2.3 MaxEnt

Model development involves both biological data and environmental data. Bioclimatic variables at a resolution of 1 km^2 from Worldclim (www.worldclim.org) were used as the environmental layers to assess the potential distribution of the selected species with maximum entropy modelling software (Maxent version 3.4.4) [28, 29]. MaxEnt is a machine learning method for making predictions or inferences from incomplete information. The algorithm is suitable for presence-only data and can deal with small samples and sampling bias [28]. Using ArcGIS (ArcMap 10.4.1), all bioclimatic variables were extracted to the area of interest (Table 1). The spatial correlation technique was performed to recognise suitable environmental layers impacting the distribution of *Dipterocarpus indicus*. MaxEnt minimizes the relative entropy between two probability densities (estimated from presence data and landscape) defined in feature (covariate) space [30]. The algorithm extracts background data from the landscape and contrasts them against the presence locations.

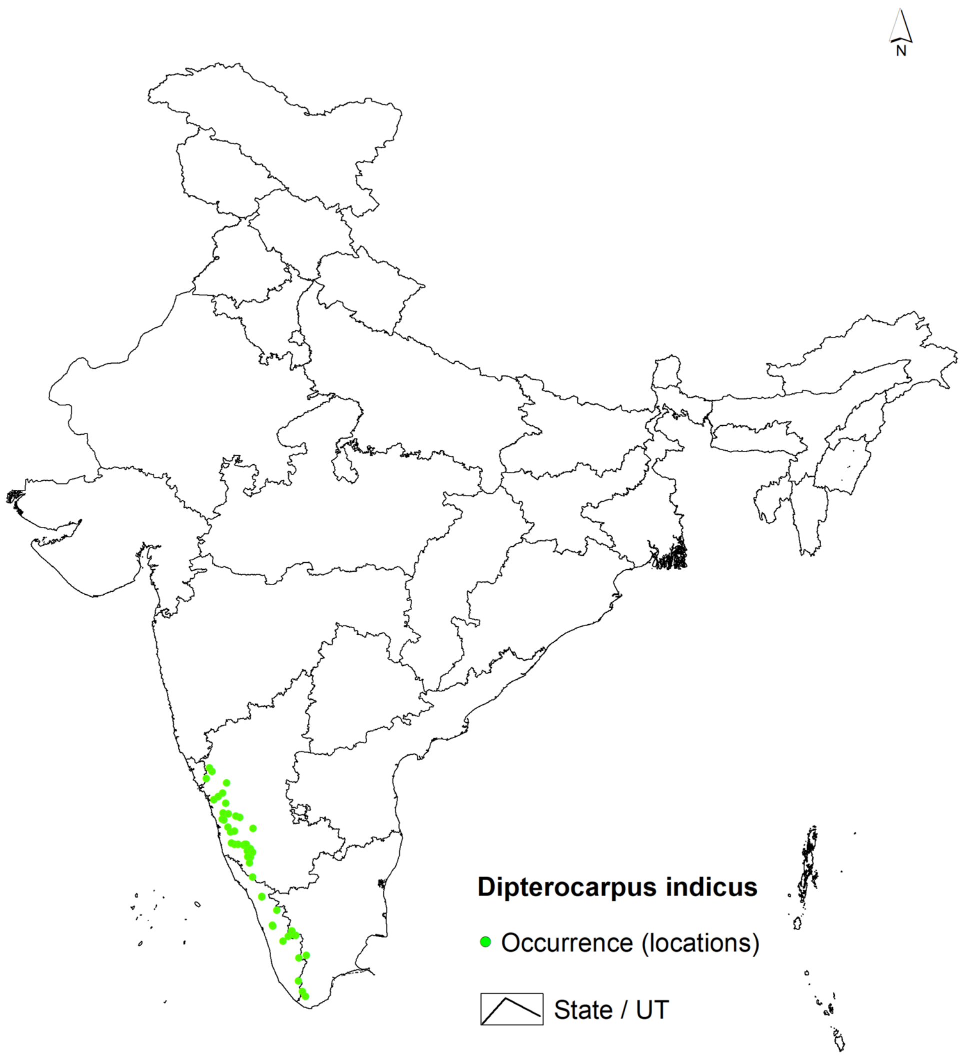

Fig. 1 Map showing occurrence points of *Dipterocarpus indicus* Bedd. in Western Ghats, India

Fig. 2 *Dipterocarpus indicus* associated low elevation wet evergreen forest, Kodachadri Hills, Karnataka (*Dipterocarpus indicus–Diospyros candolleana–Diospyros oocarpa* type)

Table 1 List of 19 bioclimatic variables used in bioclimatic-envelope model development. Names and descriptions are based on WorldClim

Code	Environmental variables	Unit	Temporal scale
Bio1	Annual mean temperature	°C	Annual
Bio2	Mean diurnal range (mean of monthly (max temp–min temp)	°C	Variation
Bio3	Isothermality (Bio2/Bio7) (× 100)	–	Variation
Bio4	Temperature seasonality (standard deviation × 100)	CV	Variation
Bio5	Max. temperature of warmest month	°C	Month
Bio6	Min. temperature of coldest month	°C	Month
Bio7	Temperature annual range (Bio5–Bio6)	°C	Annual
Bio8	Mean temperature of wettest quarter	°C	Quarter
Bio9	Mean temperature of driest quarter	°C	Quarter
Bio10	Mean temperature of warmest quarter	°C	Quarter
Bio11	Mean temperature of coldest quarter	°C	Quarter
Bio12	Annual precipitation	mm	Annual
Bio13	Precipitation of wettest month	mm	Month
Bio14	Precipitation of driest month	mm	Month
Bio15	Precipitation seasonality (coefficient of variation)	CV	Variation
Bio16	Precipitation of wettest quarter	mm	Quarter
Bio17	Precipitation of driest quarter	mm	Quarter
Bio18	Precipitation of warmest quarter	mm	Quarter
Bio19	Precipitation of coldest quarter	mm	Quarter

$$\Pr(y = 1|z) = f1(z)\Pr(y = 1)/f(z)$$

The equation above shows that if the conditional density of the covariates is known at the presence sites, $f1\ (z)$, and the density of covariates across the study area (z) are also known, then the prevalence Pr ($y = 1$) is needed to calculate the conditional probability of occurrence [11].

It uses 75% for calibration of the presence only data and the other 25% for validating the model with the bootstrapping procedure with 10 replications and a maximum of 500 iterations. The model has been validated by calculating the AUC using Receiver Operating Characteristics (ROC) analysis. In addition, model performance has been evaluated using the published field literature. Finally, the extent of the potential distribution of species has been analysed concerning the occurrence of species and associated vegetation types.

3 Results

3.1 Predictive modelling

MaxEnt is more consistent between models (low variability) but maintains a probability of the presence of around 0.5. The area under the Receiving Operator Curve (AUC) estimates the model's accuracy levels, and the greater AUC value was considered the suitable model to identify the research problem. In the study, the Jackknife method was used to calculate the significance of the variables. The resulting potential species distribution map ranged from 0 to 1 (Fig. 3). All the presence locations fall under the predicted climatically suitable habitats.

3.2 Bioclimatic envelope across the sites

Among potential distribution areas, the highest fractional predicted area was in the low elevation wet evergreen forest region between 50 and 700 m, followed by the mid-mountain region (700–1412 m). The majority of species' potential distribution was predicted inside and outside protected areas. The Uttara Kannada (North Canara), Chikmagalur, Shimoga (Shivamogga) and Kannur supported the largest area of potential distribution (Fig. 4). Research has revealed a high suitability range in mean annual precipitation between 3000 and 4500 mm. The environmental similarity of variables is used for training the model. The distribution analysis output on the prediction value is prepared using ArcMap with an overlay of species occurrence (points) and state and district boundaries.

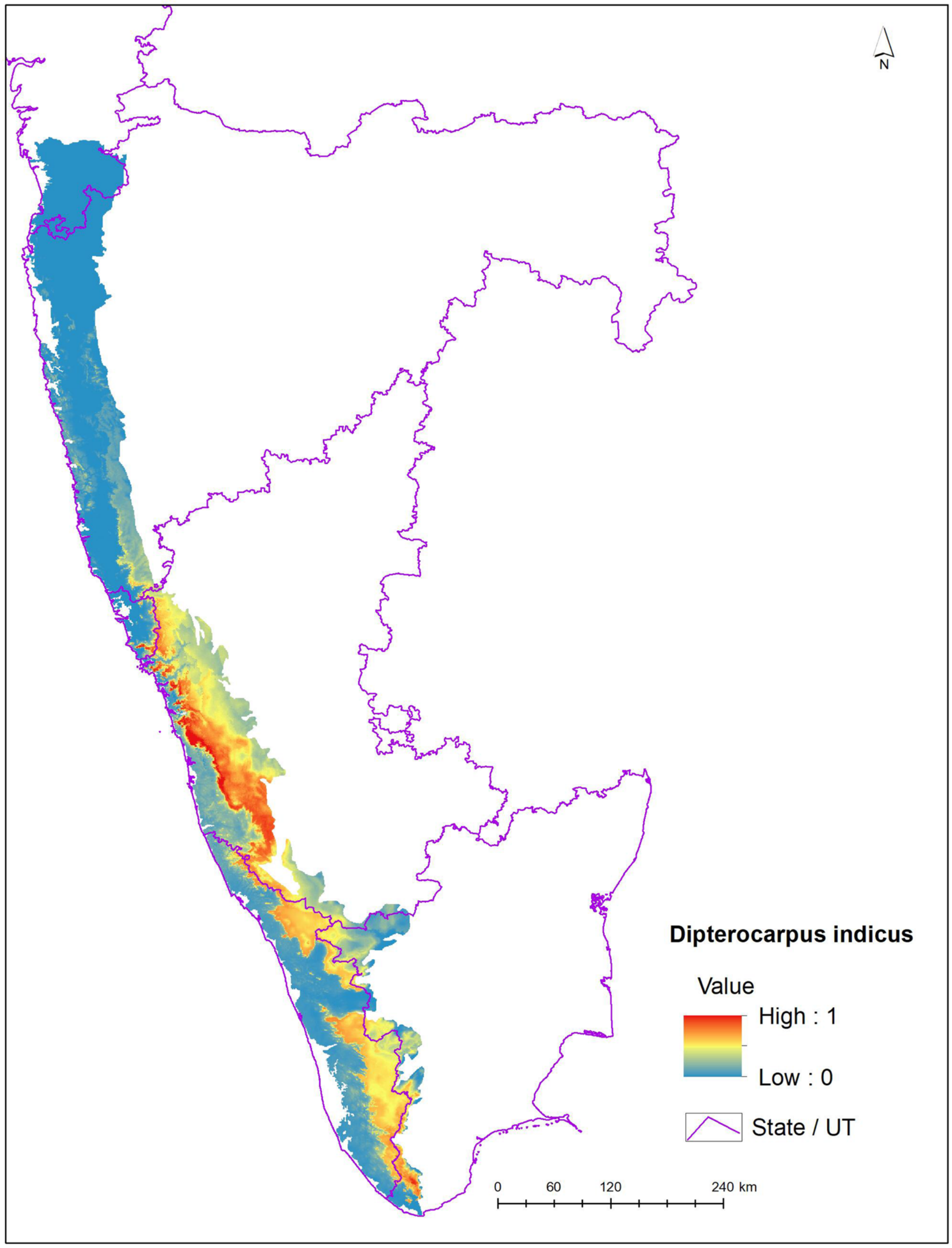

Fig. 3 MaxEnt output showing the predicted potential habitats of species at the state level

The Protected Areas of Karnataka (Kudremukh, Mookambika, Pushpagiri, Sharavathi Valley, Shettihalli and Someshwara), Kerala (Parambikulam, Peechi-Vazhani, Shendurney, and Thattekadu Bird) and Tamil Nadu (Indira Gandhi (Anamalai)), Kalakad, Mundanthurai and Kanyakumari) have represented highly suitable hábitats in the Western Ghats.

3.3 Analysing the variable contributions

Response curves for each variable in Maxent model is identified and observed to check the probable distribution of *Dipterocarpus* species to different bioclimatic variables. These plots reflect the predicted suitability of the selected variable and the dependency induced by correlations between the selected variable and other variables.

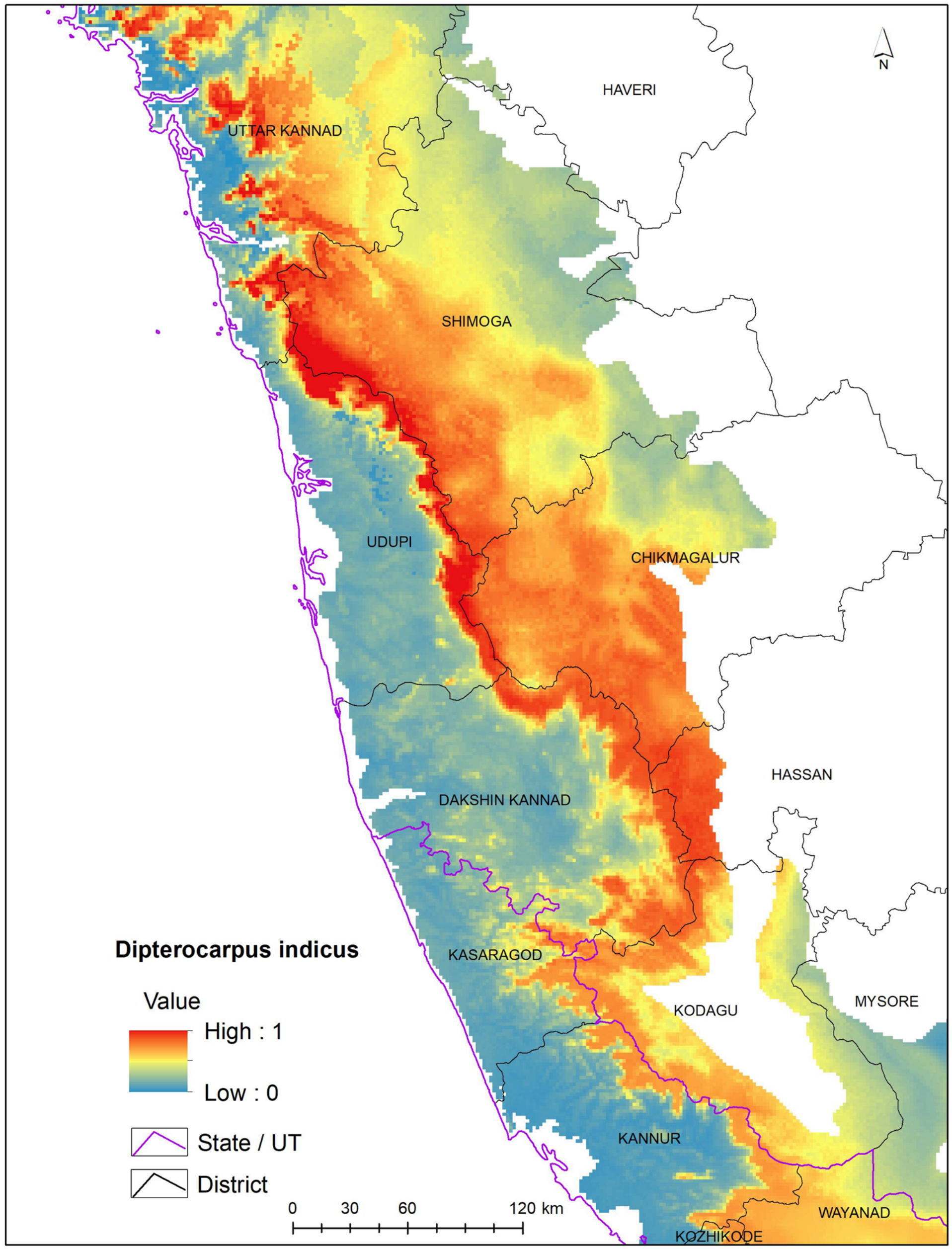

Fig. 4 MaxEnt output showing the high suitable areas at the district level in Karnataka and Kerala

The contributions of the variables in the model (Table 2) showed that precipitation of the coldest quarter (BioClim 19) was the most influential (34.3%), followed by annual mean temperature (BioClim 1) (27.1%) and Annual Precipitation (BioClim 12) (10.4%). The results of the jackknife test (leave one out) of variable importance are given in Fig. 5. The mean diurnal range (BioClim 2) is the environmental variable with the highest gain when used in isolation. Conversely, precipitation of the driest quarter (BioClim 17) is the environmental variable that declines the gain when omitted, which therefore shows to have the information that is not present in the other variables. Figure 6 is the receiver

Table 2 Analysis of variable contributions

Code	Variables	Percent contribution
Bio19	Precipitation of coldest quarter	34.3
Bio1	Annual mean temperature	27.1
Bio12	Annual precipitation	10.4
Bio18	Precipitation of warmest quarter	4.9
Bio2	Mean diurnal range	4
Bio11	Mean temperature of coldest quarter	4
Bio7	Temperature annual range (Bio5–Bio6)	3.6
Bio13	Precipitation of wettest month	3.1
Bio17	Precipitation of driest quarter	2.7
Bio3	Isothermality (Bio2/Bio7) (×100)	2.3
Bio16	Precipitation of wettest quarter	1.3
Bio14	Precipitation of driest month	0.8
Bio15	Precipitation seasonality (coefficient of variation)	0.7
Bio6	Min. temperature of coldest month	0.6
Bio4	Temperature seasonality (standard deviation × 100)	0.1
Bio8	Mean temperature of wettest quarter	0.1
Bio9	Mean temperature of driest quarter	0.1

operating characteristic (ROC) curve for the same data. In this study, the AUC of the constructed model based on the potential climatic factors affecting species distribution was 0.894 for training data and 0.846 test data, respectively. This AUC value specifies that the constructed model is appropriate and has good predictive accuracy. Hence, it is suitable for modelling the geographic distribution of *Dipterocarpus indicus.*

3.4 Validation of highly suitable areas with field inventories

The resultant output on species distribution matches with the published literature on abundance information. In Karnataka, the tree species are common in the wet, evergreen forests of Dakshina Kannada, Chikmagalooru, Kodagu (Coorg), Hassan, Shivamogga (Shimoga) and Uttara Kannada forests [31–34]. In Tamil Nadu, it was reported as common species in wet evergreen forests of Anamalais of Coimbatore district [35–37]. MaxEnt predicted these areas as highly suitable environments (> 0.5 value) for the distribution of *Dipterocarpus indicus.*

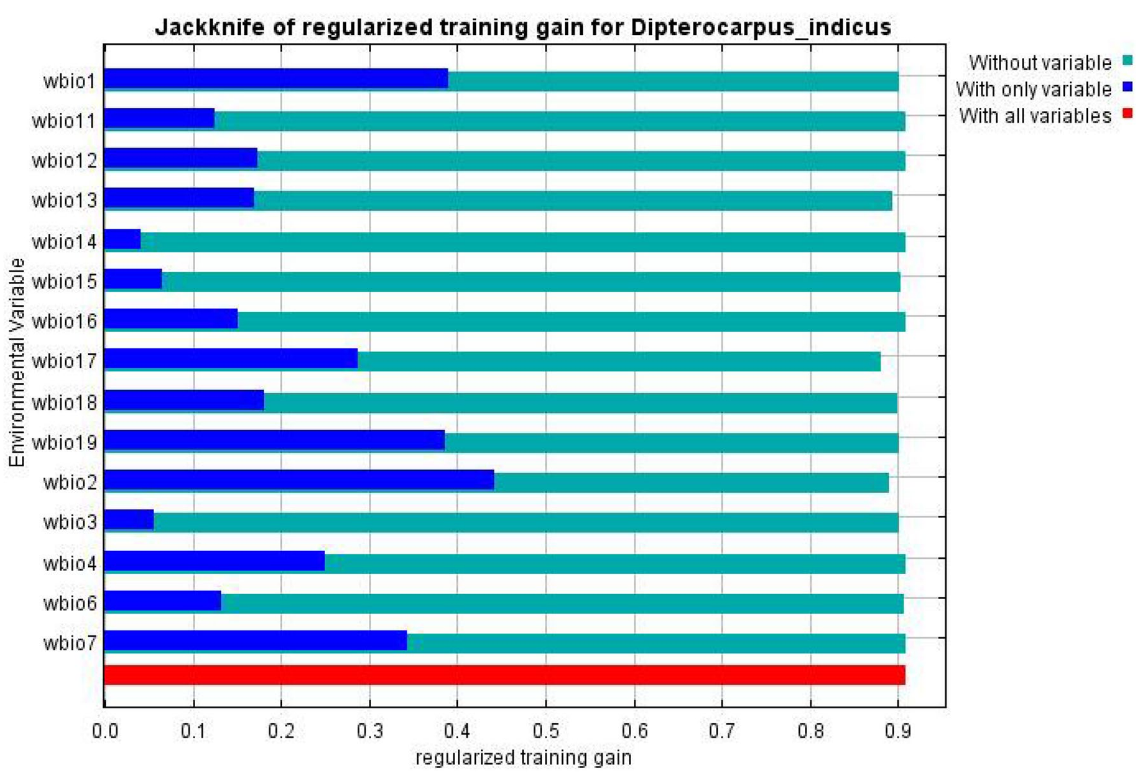

Fig. 5 Jackknife of regularised training gain for *Dipterocarpus indicus*

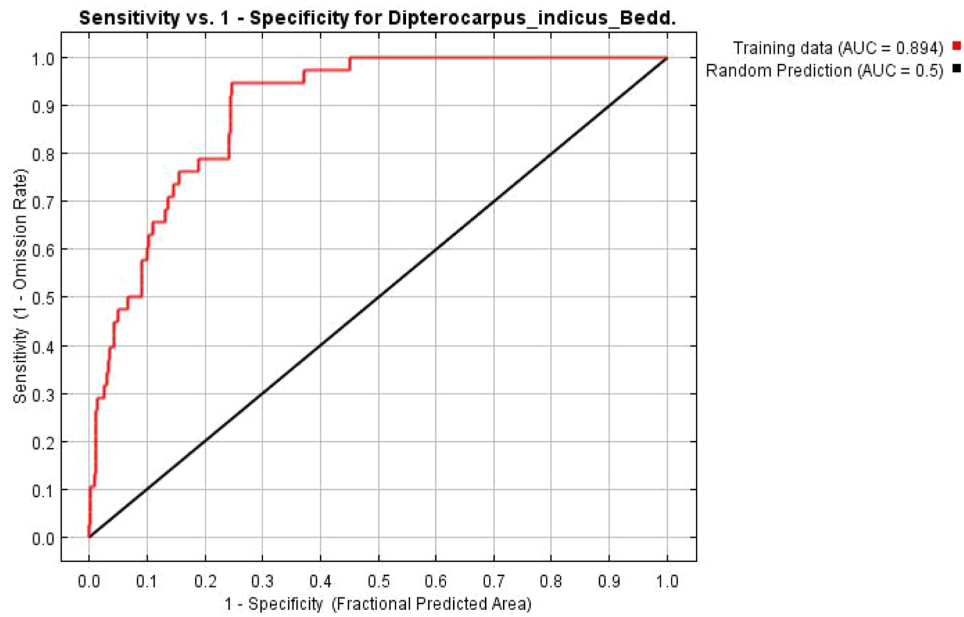

Fig. 6 ROC curve of sensitivity versus specificity

4 Discussion

Considering the distribution of *Dipterocarpus indicus,* an endemic and endangered species, it is noted that it is mostly adapted to tropical evergreen and semi evergreen forests of Western Ghats. Suitable precipitation range of values might be important for luxurious growth and distribution of species [38]. During the analysis, the influence of the 19 bioclimatic variables have been studied and observed that four major variables are influencing in their response curves for the *Dipterocarpus* species (Isothermality, Min Temperature of Coldest Month, Annual Precipitation, and Precipitation of Warmest Quarter) related to precipitation changes [Supplementary Material]. The correlation between distribution of selected species and bioclimatic predictor variables has shown a clear association with temperature, precipitation and other climatic variables, as reported by [14]. Thus specific climatic variables play critical role in ecological niche of this *Dipterocarpus* species.

The predicted values fall within the range compared with the study [39] on *Dipterocarpus turbinatus* in the Mahananda wildlife sanctuary of North Bengal. More than 97% of model accuracy was reported for *Dipterocarpus turbinatus* by [40] from Bangladesh. Among the predictor variables, the annual temperature range (Bio7) was contributed to the highest (64.6%) for *Dipterocarpus turbinatus.* The AUC and Kappa statistics value for *Dipterocarpus littoralis* was reported as 0.91 ± 0.062 and 0.37 ± 0.025 by [41] in Nusakambangan, Indonesia. Environmental variables that significantly contribute to *Dipterocarpus littoralis* in Nusakambangan are the distance from the coastline and elevation [41]. Maxent model on fourteen different threatened forest tree species in Phillippines was reported by [42], ranging the ROC AUC values from 0.7 to 0.97. The study by [43] focused on using ecological niche models to assess the conservation status of *Dipterocarpus lamellatus* and *Dipterocarpus ochraceus.* The work of [43] reported the Kappa statistics value for *Dipterocarpus lamellatus* and *Dipterocarpus ochraceus* in Sabha, Malaysia, as 0.47 and 0.39, respectively. Chen et al. [44] has demonstrated the importance of each variable in adaptations of endemic plant species *Paeonia mairei.* The *Dipterocarpus bourdillonii* is distributed in southern part of Western Ghats [45]. The spatial data of protected area boundaries was found useful in identifying the highly suitable areas of *Dipterocarpus indicus* in Western Ghats [46].

Conservation strategies that are specific to the climatic variables, ecological characteristics, spatially explicit ecological niche and monitoring of the population structure are useful in identifying habitats for species recovery and restoration. In the present study MaxEnt model was used since it has proved to be efficient in predicting the habitat suitability and estimating the potential geographic distributions of a species of interest. *Dipterocarpus indicus* is also known to occur in small populations due to fragmentation and this has lead to inbreeding depression and floral abortion [34]. The low stand density of *D. indicus* reduces the inter-tree movement of pollens, encourages self-pollination and ending in low outcrossing rate. The *D. indicus* associated forest is one of the major habitat for the critically endangered lion-tailed macaque (*Macaca silenus*) [34]. Climate change at the global level and anthropogenically induced pressures at local level are influencing the distribution and survival of narrow niched species. Understanding of species distribution models can benefit long-term conservation through their link with spatial decision support system and policy.

5 Conclusion

This study attempts to understand the potential distribution of *Dipterocarps indicus*. Precipitation of the coldest quarter (34.3%) and annual mean temperature (27.1%) has played a crucial role in the distribution of the endemic species. The study's findings can be used to identify suitable localities for ecological restoration and input for management plans. The MaxEnt model predicted the landscape level information in a spatially explicit way. The future scope of this work is to study the impact of future scenarios of climate change on the spatial distribution of *Dipterocarpus indicus,* which will be a crucial input for conservation planning.

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Data availability All the data generated or analysed during this study are included in this published article (and its supplementary information files).

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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