Can the distribution of sal (*Shorea robusta* Gaertn. f.) shift in the northeastern direction in India due to changing climate?

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Sal (*Shorea robusta* Gaertn. f.) is a dominant tree species, whose natural range lies between 20–32°N lat. and 75–95°E long., is spread across 10 million ha in India. Species distribution models predict the species geographic ranges from occurrence records and site-specific environmental data. Here, we have (i) generated the 1960s scenario for sal species on the basis of the existing published literature; (ii) confirmed the species occurrence data using satellite imagery for the period of 1972–75; (iii) run the Maxent species distribution model to predict the distribution for the year 2020 under climate change scenario SRES A1-B and (iv) validated the prediction using more than double the amount of species occurrence data gathered during the last decade (1998–2008). The model identified moisture as the key player that would influence the distribution to shift towards northern and eastern India, with greater than 90% certainty. The study highlights utility of the archived remote sensing data in providing locational information in climate change studies.

Keywords: Climate change scenario, maximum entropy method, species distribution model, timber species.

Introduction

SAL forests are spread across 10 million hectare (m ha) in India. Sal as an important tree species with high timber value[1]. Globally, the natural range of sal forests lies between 20–32°N lat. and 75–95°E long., where the distribution is primarily controlled by climate and edaphic factors[2]. In India, the species is dominantly distributed on the plains and lower foothills of the Himalayas and also along the valleys[3]. Champion and Seth[4] have demarcated the spread of sal forests ranging from Uttarakhand in the north up to Andhra Pradesh in the south and Tripura in the east; covering Himachal Pradesh, Haryana, Uttar Pradesh (UP), Bihar, West Bengal, Odisha, Madhya Pradesh, Chhattisgarh, Maharashtra, Jharkhand, Sikkim, Assam and Meghalaya (Figure 1). The forests are distributed dominantly on alluvium, along with that on ancient crystalline rocks, Gondwana and Vindhyan soils[4]. The tree is moderate to slow growing and can attain heights of 30–50 m with a diameter of 3–3.5 m. The bole is clean, straight and cylindrical, but often bearing epicormic branches; crown is spreading and spherical (Figure 1 *a*). The bark is dark brown and thick, which provides effective protection against fire. The tree develops a long tap-root at an early stage of growth. Leaves are simple, shiny, glabrous, approximately 10–25 cm long and broadly oval at the base, with the apex tapering into a long point. Leaf shedding takes place approximately between February and April, and leaf burst begins in April and May. Flowers are yellowish-white, arranged in large terminal or axillary racemose panicles; fruits at full size attain 1.3–1.5 cm length and 1 cm diameter. It is surrounded by segments of the calyx enlarged into five rather unequal wings about 5–7.5 cm long. Natural regeneration takes place by seeds, but is often affected by anthropogenic disturbances. Timilsina *et al.*[5] and Pandey and Shukla[6] observed a poor rate of regeneration via seeds under higher degree of human interference and activities such as burning and forest-cutting. Sal forests form a major source of timber and are managed for commercial timber production to increase revenue[2]. During the past decades, there was massive deforestation to use the wood as railway sleepers, ship-building and other purposes. Past records provide evidence of larger distribution of sal forests in the northern and eastern parts of India[7], and their eventual clearance for expanding agriculture, human settlements, etc.[8]. Sal forests yield non-timber forest products, including fodder[9], seed for oil, tannin and gum from bark[10] and leaves for plate-making.

Sal forests occur in consociation and/or association based on location, climatic conditions and interspecific exchanges. The usual associate species of sal in the top canopy in the Terai region of UP are *Terminalia alata* W&A (asna), *Syzygium cumini* Linn Skeels (jamun), *Anogeissus latifolia* Wall. (dhau) and *Adina cordifolia* Hk. f. (haldu). Chitale *et al.*[11] have attempted to identify, classify and map nine sal communities in the terai landscape in UP, whereas Pandey and Shukla[12] measured the diversity of sal forests in Gorakhpur and found that natural forests are highly diverse compared to the plantations.

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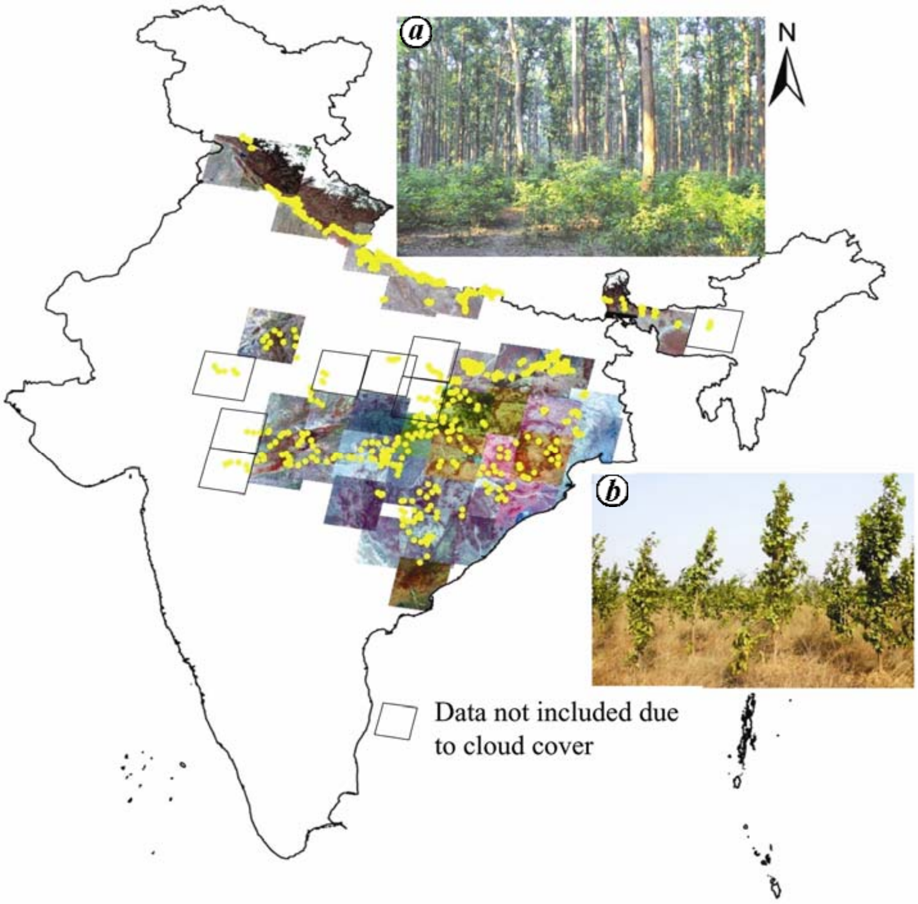

Figure 1. Spatial distribution of *Shorea robusta* Gaertn. f. in India. Information of 1961–62 overlaid on satellite imageries during 1972–75: (Inset) ***a***, Field photograph showing sal mixed forest in the Katarniaghat Wildlife Sanctuary, Uttar Pradesh; ***b***, Sal plantation conserved by local villagers and forest department near Kharagpur, West Bengal.

Singh and Kushwaha[13] studied the phenology of the sal forests in Sonbhadra District, UP and highlighted the adaptability of the species. Gautam *et al.*[14] assessed the critical loads in sal forests in Doon valley. Although various researchers have attempted to study the sal forests, only few of the studies have utilized advanced geospatial tools and techniques. Satellite data serves as an important tool in mapping and monitoring of forests due to its low cost, easy availability, better temporal and spatial resolution that ultimately minimizes the time and cost of field-based surveys. Recently, medium resolution archive satellite data has given a boost to remote sensing-based studies due to free availability[15].

Climate has significant influence on the distribution, structure and ecology of the forests[16–18]. It is evident from the projections of global models that as a result of changes in temperature, precipitation and soil moisture availability due to increase in greenhouse gases, majority of the forests will undergo shifts. Certain climatic regimes are associated with particular plant functional types[19–22], hence it is reasonable to assume that changes in climate would alter the distribution pattern and composition of forest ecosystems. The Maxent species distribution models (SDMs) dealing with presence only data, were proven to be advantageous over the methods considering presence/absence data[39,40]. Maximum entropy method is a general-purpose machine learning method with a simple and precise mathematical formulation. Maxent is a bioclimatic model which deals with presence only data and has a number of aspects that make it well-suited for species distribution modelling[40]. Various researchers have implemented Maxent to predicting the species distribution of endangered and threatened species. Phillips *et al.*[40] implemented the Maxent model to predict the distribution of *Bradypus variegatus* and *Microryzomys minutus* in Andes mountains, whereas Kumar *et al.*[41] predicted the distribution of threatened and endangered tree species, *Canacomyrica monticola* in New Caledonia.

Recent studies have been conducted to assess the impacts of climate change on forests in India, which cover approximately 21% of the total geographical area of the country[23–25]. Ravindranath *et al.*[25] showed that 77% and 68% of the forested grids in India are likely to experience shift in forest types for climate change under A2

Table 1. Methodological steps

Activity	Steps	Output
Distribution of sal (*Shorea robusta* Gaertn. f.) forests with respect to the 1960s scenario	Gathering occurrence from Champion and Seth[4] (Table 2)	Confirmation of locational information of the target species from satellite data (1972–1975)
Distribution of sal for the year 2020 (SRES A1-B scenario)	Species distribution of sal in India using maximum entropy (Maxent) model	Map with probable distribution of sal species
Validation of model prediction using field distribution points	GPS-based locations from 'Biodiversity characterization at landscape level' project gathered during 1998–2008 were utilized	From a practical point of view, the field sampling locations serve as the best alternative to judge if the prediction holds good till date and at what level of confidence
Analysis of prediction scenario	Analysing the training and testing gain; and area under curve	The predicted change scenario in distribution pattern in India during 60 years (1960–2020)
Sensitivity analysis for predictor variables used in the Maxent model	Analysing the role of each environmental variable in predicting the species distribution in India	Contribution of each environmental factor and the crucial ones were identified

and B2 scenarios respectively, whereas Chaturvedi *et al.*[26] concluded that 39% and 34% of the forested grids in India are likely to experience shift in forest types under A2 and B2 scenarios respectively, by the end of this century. Few other studies indicated moderate to large-scale shifts in vegetation types with implications for forest die-back and biodiversity[27,28]. Although studies have indicated the potential impacts of climate change on forests in India, they suffer from limitations such as most of them had coarse resolution of model output, limited capability in categorization of plant functional types and only a few were able to capture the shifts at species level. Due to global warming by 1–2°C, most ecosystems and landscapes will be altered through changes in species composition, biodiversity and productivity[29] and would exhibit peculiar patterns of distribution. Thus, assessing the likely impacts of projected climate change on forests, particularly at the species level, is the need of the hour. The concern has resulted in an immediate action for formulation of SDMs to predict the fate of vulnerable species under future climate scenarios. SDMs that incorporate future climate predictions are a popular way to address the questions concerning the distribution of the species. Predictive modelling of species distribution represents an important tool in biogeography, ecology and biodiversity studies[30,31]. SDMs attempt to predict the species geographic ranges from occurrence (presence only or presence/absence) records and site-specific environmental data[32–34]. Recently, majority of the studies have been conducted to predict the probable distribution of shrub or herb species as the shifts would be more evident in these cases, but only few studies have been attempted for tree species, which are an important source of timber wood[35–37].

The present study attempts to assess the changes in distribution pattern of sal in India, based on maximum entropy (Maxent) model with presence only data of the 1960s for SRES A1-B scenario for the year 2020. The species was selected due to its economic importance, ecological significance and dominance as a top canopy species. Although sal forests can survive in cooler and warmer temperatures, it would be difficult to modify the phenological cycle to maintain the semi-evergreen habit under temperature rise during future years. The forests would tend to shift to suitable areas to maintain the survival rate and proper growth. The study area is situated between 08°N and 38°N lat. and 66°E and 100°E long. and covers an area of approximately 329 m ha. India experiences four distinct monsoonal periods, viz. southwest (SW) summer monsoon (June–August), northeast (NE) winter monsoon (December–February), spring (March–May) and autumn (September–November)[38]. The large spatial variability in monsoonal activity is the main reason for diverse vegetation types across the country. Here, we have utilized the archive data of Landsat MSS (Multispectral scanner) for 1972–75 to identify the sal species locations based on the information collected (Tables 1 and 2)[4]. A nation-wide study on 'Biodiversity characterization and landscape level' and the generated database provide prospects for further ecological and biodiversity studies[16]. The field sampling carried out during the execution of the project in last decade (1999–2009) provided 2040 locations for the occurrence of sal species in India, which were utilized for validation of species distribution predicted by the Maxent model for the year 2020. The prediction scenario was analysed with respect to the environmental variables and the level of confidence (Table 1).

Model parameterization

Target species and occurrence data

One thousand and four occurrence points of sal species with respect to 1960s were generated[4] and supplemented by satellite image-based identification and confirmation (Figure 1). Table 1 provides the details of the steps followed. Criteria-based selection was implemented to select the target/indicator species. The criteria were based on economic importance, local uses, climate adaptability and the distributional dominance of the species.

Predictor variables

The variables were chosen based on their ecological relevance to plant species distribution and past SDM studies[43]. The datasets pertained to both the current period and the future climate change scenario (HadClim emission scenario SRES-A1B) for 2020. The year 2020 was selected as prediction year because the responses of climate change would be clearly evident by that instance[44]. Nineteen bioclimatic variables were obtained from WorldClim dataset[45] (http://www.worldclim.org/bioclim.htm). Elevation (digital elevation model; DEM) data were obtained from the USGS website (http://www.usgs.gov.in/#/Find_Data/Products_and_Data_Available/SRT); 1 km spatial resolution, finally all environmental variables and ancillary layers were resampled to 1 km spatial resolution.

Modelling approach

Maximum entropy method was implemented to analyse the distribution of *S. robusta* Gaertn. f. under future climate change scenario for the year 2020. The model was formulated by Phillips[40] and first implemented over the Amazonian region. The present study used the free version of Maxent software, version 3.3.3e (http://www.cs.princeton.edu/~schapire/maxent/), which generates an estimate of probability of presence of the species that varies from 0 to 1, i.e. from the lowest to the highest probability. The receiver operating curve (ROC) describes the relationship between the proportion of correctly predicted observed presences, i.e. sensitivity and the proportion of incorrectly predicted observed absences, i.e. 1-specificity. A precise prediction model generates a ROC that follows the left axis and top of the plot, whereas a model with predictions worse than a random model will generate a ROC that follows the 1 : 1 line.

Testing and validation

It is recommended to validate model predictions prior to any extrapolation or interpretation[46]. Ideally an independent dataset should be used for testing the model performance. Here, 2040 field sample location points were provided by the Indian Institute of Remote Sensing (IIRS/ISRO), Dehradun. We followed the jackknife (also called 'leave-one-out') procedure and the results were obtained in the form of three graphs, viz. (i) regularized training gain, (ii) testing gain and (iii) area under curve indicating the significance of the environmental variables together and also as individual cases. The graphs for omission and predicted area and sensitivity versus 1-specificity were obtained to analyse the predicted fractional area to judge the performance of the model against the random prediction. The specificity graph shows omission on training samples (blue line), omission on test samples (cyan line), predicted omission (black line) and fraction of predicted background (red) (Figure 2 *a*). The graph for fractional predicted area (FPA), i.e. 1-specificity shows the performance under training data (red line), test data (blue line) and random prediction (black line).

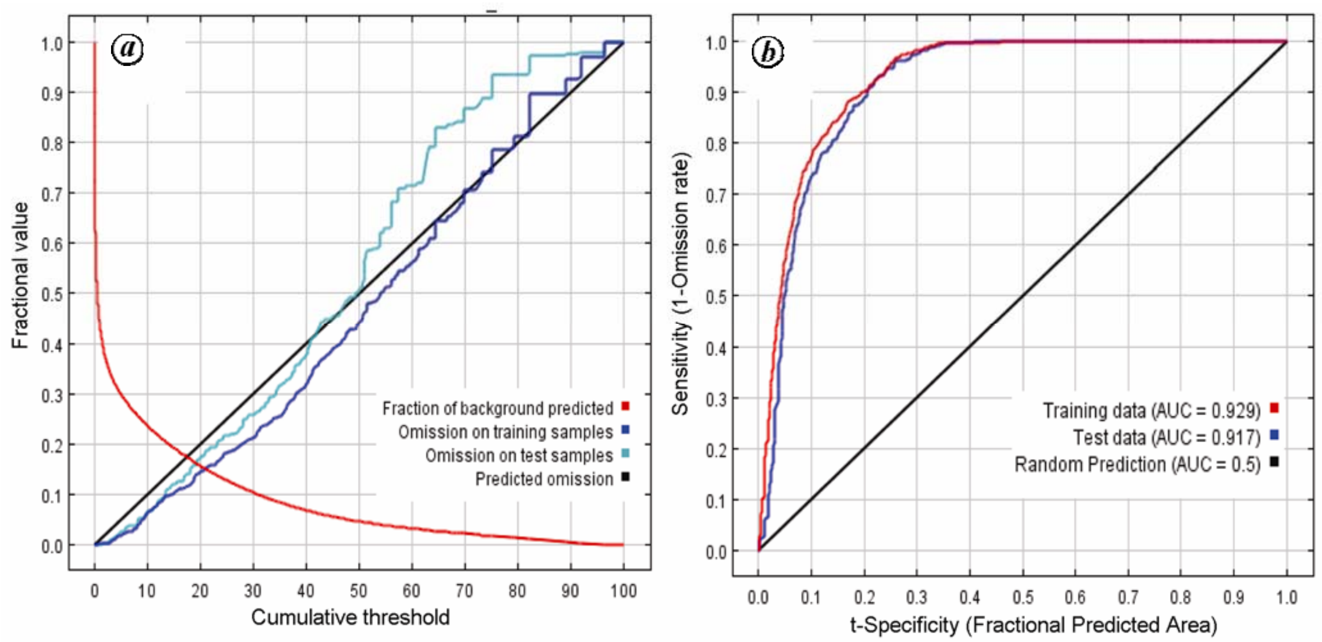

Figure 2. ***a***, Omission and predicted area; ***b***, Sensitivity versus 1-specificity of *S. robusta* Gaertn. f.

Table 2. Distribution and characteristics of sal forests in India (source: Champion and Seth[4])

Champion and Seth[4] vegetation-type		Distribution: State	Distribution: Division	Locality factors	Associate species
3C/C1	Very moist sal-bearing forest	Assam (currently Meghalaya), Odisha West Bengal	Garo, Khasi, Mikir and Jaintia hills Anugul and Puri; Eastern sub-Himalayan Bhabar-Tarai and plain tracts	Occurs on red and lateritic soils	*Alpinia* spp., Bamboos are more general
CIa	Eastern hill sal forest			Many different rocks	*Schima wallichii*, *Dendrocalamus hamiltonii*
CIa (i)	Eastern Himalayan sal	West Bengal	Teesta valley slopes	Rainfall: 3800 mm	
CIa (ii)	Khasi hill sal	Assam	Kamrup division	Gravelly on crests and upper slopes	
CIb	Eastern bhabar sal			Alluvial loamy soil	
CIb (i)	Eastern Himalayan upper bhabar sal	West Bengal, Assam	Kurseong and Buxa division	Alluvial soil with boulders	*Lagerstroemia parviflora*, *Aphanamixis polystachya*
CIb (ii)	Eastern Himalayan lower bhabar sal	West Bengal, Assam	Bamanpokhri and Buxa division	Alluvial 260 m upwards	*Terminalia tomentosa*, *Machilus* spp.
CIc	Eastern Terai sal	West Bengal, Assam	Buxa and Goalpara west division	Dark alluvium and khurkhani soil	*Michelia champaca*, *Themeda arundinacea*
CId	Peninsular sal	Odisha	Puri	Occurs on well-drained ridges and slopes	*Dillenia pentagyna*, *T. tomentosa*
3C/C2	Moist sal-bearing forest			Rainfall: 1400–1900 mm	
C2a	Moist Siwalik sal	Uttarakhand, Uttar Pradesh	Siwalik hills/Haldwani division Saharanpur	Nahan sandstone with light soil	*A. latifolia*, *T. tomentosa*
C2b	Moist bhabar sal			Good loamy soils	*T. tomentosa*, *L. parviflora*
C2b(i)	Bhabar–dun sal	Uttarakhand	Dehradun, Kumaon Bhabar		*Adina cordifolia*, *Litsea glutinosa*, *T. bellerica*, *Ficus* sp.
C2b(ii)	Damar sal forest	Uttar Pradesh	North Kheri		*Adina cordifolia*, *Syzygium cumini*, *T. tomentosa*, *A. cordifolia*
C2c	Moist Terai sal	Uttarakhand	Haldwani	Grey clayey alluvium with wet subsoil	*Syzygium cumini*, *Trewia nudiflora* *Elaeagnus latifolia*, *Bambusa arundinacea*
C2d	Moist plains sal				
C2d(i)	West light alluvium plains sal	Uttar Pradesh	North and south Kheri	Sandy alluvium with dry subsoil	*T. tomentosa*, *T. bellerica*, *Butea monosperma*, *Bauhinia mallabarica*, *Madhuca indica*, *Buchanania lanzan*

(*Contd*)

Table 2. (*Contd*)

Champion and Seth[4] vegetation-type		Distribution: State	Distribution: Division	Locality factors	Associate species
C2d(ii)	Chandar sal	Uttar Pradesh	Pilibhit	Low lying Chandars	*Syzygium cerasoideum*, *Themeda arundinacea*
C2d(iii)	Eastern heavy alluvium plains sal	Uttar Pradesh, Assam	Gorakhpur,	Yellow clayey alluvium	*Terminalia tomentosa*, *Dillenia pentagyna*, *T. bellerica*, *T. chebula*
			Guma/Goalpara west division	On red soils overlaying boulder deposits	*Amoora wallichii*, *Gmelina arborea*
C2d(iv)	Kamrup sal	Assam	Kamrup division	Yellow clayey alluvium and khurkhani soils	*Dillenia pentagyna*, *Careya arborea*
C2e	Moist Peninsular sal forest			Crystalline rocks with yellow soils	
C2e(i)	Moist Peninsular high level sal forest	Odisha, Madhya Pradesh	Kalahandi, Supkhar	Hills on laterite trap and crystalline rocks	*Syzygium cumini*, *Dendrocalamus strictus*, *Albizzia chinensis*, *Cedrela toona*
				Occurs on deep loam, black soil, laterite	*Anogeissus latifolia*, *Madhuca indica*
C2e(ii)	Moist Peninsular low level sal forest	Odisha, Chattisgarh	Angul/Ghumsar division Southern Raipur	Crystalline rocks with yellow loam soils	*T. tomentosa*, *Mitragyna parviflora*, *Madhuca indica*, *T. chebula*
C2e(iii)	Moist Peninsular valley sal	Bihar Bihar Odisha Bihar	Singhbhum Saranda Upper Odisha Singhbhum	Crystalline rocks with deep loam soil	*T. tomentosa*, *A. cordifolia*
DSI	High level plateau sal Moist hill sal Valley sal Damp valley sal			On flat topped hills over 800 m Except ultrabasic rocks Ferruginous loam	*Bauhinia retusa*, *Themeda* sp. *Wendlandia* sp., *Indigofera* sp. *Moghania* sp., *Imperata* sp., *Polyalthia* sp., *Croton oblongifolius*, *Imperata* sp.
	Moist sal savannah			Throughout the Gangetic Plains	*Lagerstroemia parviflora*, *Lannea coromandalica*
	High level savannah	Assam	Kamrup division	Generally occurs in old clearings	*Careya arborea*, *Zizyphus* sp.

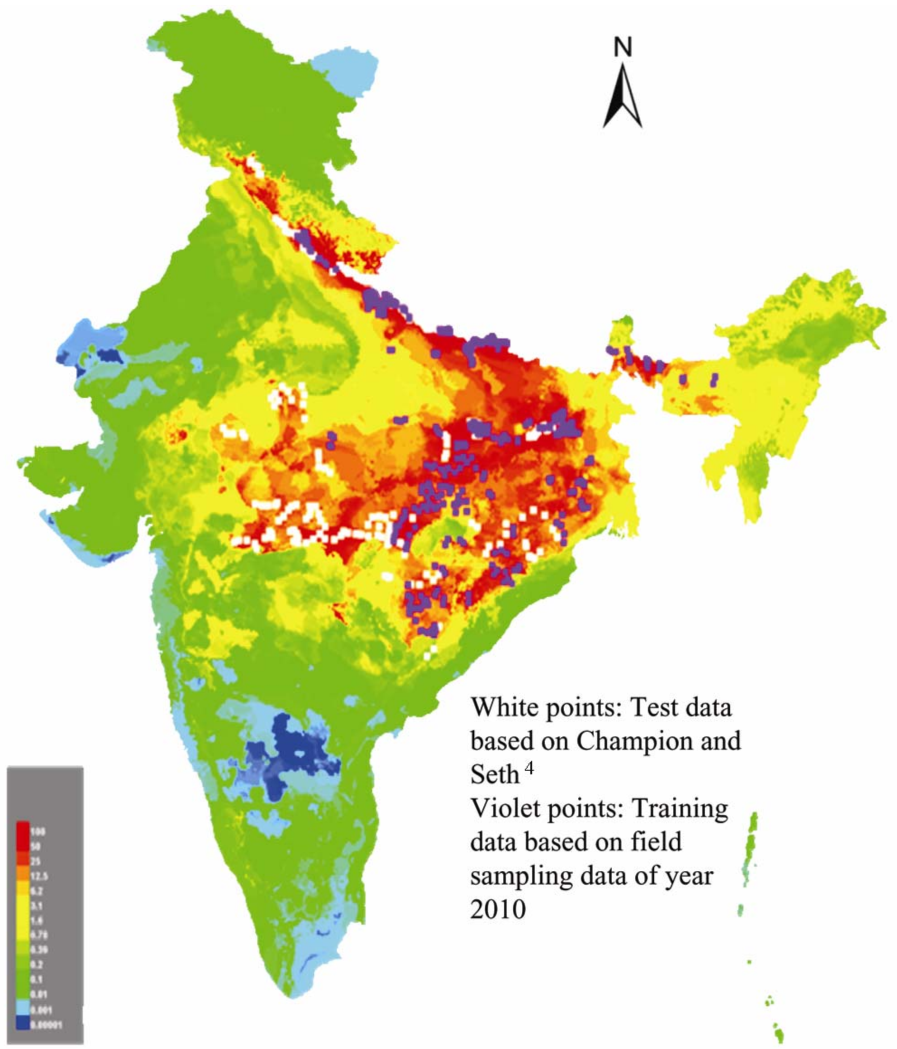

Figure 3. Maxent model based distribution of *Shorea robusta* Gaertn. f. for the year 2020.

Results

The Maxent model provided potential distribution of sal (Figure 3), which represents the logistic output of the model, wherein the probability of presence is represented as an estimate between 0 and 1. Warmer colours showed areas with better predicted conditions; red colour indicates high probability of suitable conditions for the species, whereas green colour indicates moderate conditions and lighter shades of blue indicate low predicted probability of suitable conditions. The distribution of white dots shows the locations used for training data, whereas violet dots show test locations. The model has shown probable distribution of sal during 2020 in northern and eastern India, with few patches in central and northeastern India to be moderately suitable for the species (Figure 3). In northern India, the distribution was observed in Himachal Pradesh (Siwalik hills), Uttarakhand (Siwalik hills and Bhabar regions) and UP (dominantly in the Terai region and in the Vindhyan hills), whereas in central India, it was observed in Madhya Pradesh and Chhattisgarh. In eastern India the distribution was seen in Jharkhand, Bihar, West Bengal and Odisha (Koraput and Puri districts); whereas in northeastern India, it was observed in Arunachal Pradesh, Assam and Meghalaya (Kamrup hills). In general, shifts are observed towards the eastern coast and northern part of India owing to the higher moisture content. The area under the ROC curve (AUC) is also shown in Figure 2 *a*. The red line (training) and blue (testing) line show the 'fit' of the model to the training data and testing data respectively. The red line indicates whether the model prediction was better than random. The AUC obtained for training data was 0.929 and test data was 0.917, compared to the expected AUC of 0.5 for random prediction.

Evaluation of predicted results – Jackknife plot – AUC and training gain

The AUC plot indicated temperature seasonality to be the most effective single variable for predicting the distribution

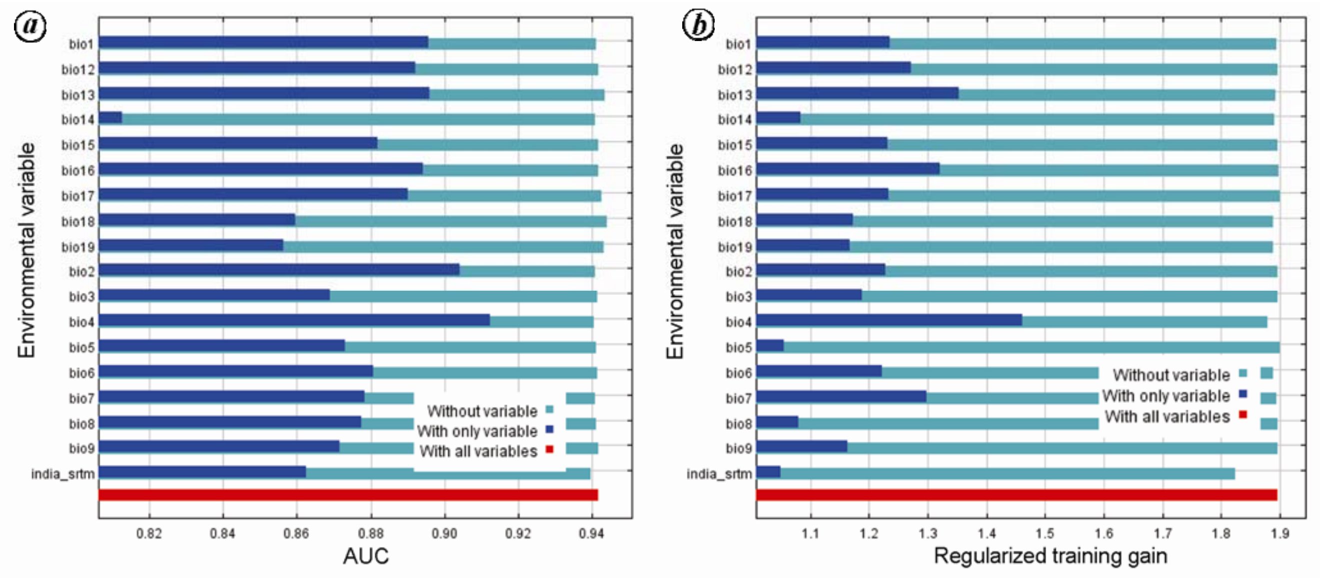

Figure 4. Jackknife of (***a***) area under the curve; (***b***) regularized training gain for *S. robusta* Gaertn. f. bio1, Annual mean temperature; bio2, Mean diurnal range; bio3, Isothermality; bio4, Temperature seasonality; bio5, Maximum temperature of warmest month; bio6, Minimum temperature of coldest month; bio7, Temperature annual range; bio8, Mean temperature of wettest quarter; bio9, Mean temperature of driest quarter; bio12, Annual precipitation; bio13, Precipitation of warmest month; bio14, Precipitation of driest month; bio15, Precipitation seasonality; bio16, Precipitation of wettest quarter; bio17, Precipitation of driest quarter; bio18, Precipitation of warmest quarter; bio19, Precipitation of coldest quarter; India_srtm; Digital Elevation Model of India.

of the occurrence data that were set aside for testing (Figure 2 *a*), when predictive performance was measured using AUC, even though it was hardly used by the model built using all the variables. The precipitation of the driest month did not show any significance in the prediction as indicated by the lowest gain shown in AUC. Comparison of the jackknife plots indicated the significance of environmental variables in the model prediction. It can be clearly seen from the plot for training gain (Figure 4) that, if the model uses only bio14, i.e. precipitation of the driest month, it achieves almost no gain, so the variable is not (by itself) useful for estimating the distribution of sal. On the other hand, bio4, i.e. temperature seasonality allows a reasonably good fit to the training data. This indicates the influence of variation in seasonal temperature on the phenological cycle of the species. As depicted by the cyan-coloured bars, it appears that temperature seasonality has a significant role in the training set-based prediction, as the absence of the variable resulted in significant decrease in gain. This indicates that decline in precipitation is the crucial factor that highlights the need of higher moisture content for species growth.

Sal forests distribution in India

The present study attempted to predict the distribution of sal forests in India for the year 2020 based on the occurrence locations provided for the 1960s by Champion and Seth[4]. The field surveys were carried out by Champion and Seth[4] during November 1961 to June 1962. The location, species composition as well as locality factors were considered to characterize the sal forests in India (Table 2). Dominant distribution was observed in northern India, especially along the Terai tract in UP, which contains humus-rich alluvial soils. The occurrence of sal forests during the 1970s (1972–1975) confirms their occurrence during the 1960s as well. The Maxent model was run using the training data for the 1960s, whereas the field data collected during 1999–2009 on sal species locations were used as test data. Then 1004 locations were used as training data, whereas 2040 sampling locations were used for testing and validation of the distribution provided by the model. As the data collected by Champion and Seth[4] were based on the field surveys and do not contain any specified boundaries for sal forests, it was not possible to get the species locations. Thus the points were confirmed on the nearest available satellite imageries of 1972–1975, thereby creating the past distribution scenario with 100% certainty for utility in the Maxent model. The field sampling data collected during 1999–2009 also indicated the presence of majority of the forest locations with respect to those during the 1960s. However, due to unavailability of cloud-free data, some occurrence locations gathered from Champion and Seth[4] could not be confirmed (Figure 1). The SDMs output on sal distribution prediction would help in providing the probable locations where the forests would tend to shift during changing climate in future scenarios, which could be utilized for better conservation and management of forested landscapes.

Discussion and conclusion

The present study utilized the existing information, i.e. literature[4], satellite data[15] and species occurrence data generated in another study[16], to generate past scenario with respect to target species and validation of future prediction scenario (Table 2; Figures 1 and 3). The AUC of 0.929 and 0.917 observed for the test and training data respectively, indicated higher success rates with low omission. It has predicted the probable distribution of the species in eastern and northeastern India owing to higher moisture content. Climate change studies have indicated that eastern and northeastern India are likely to become much wetter compared to other parts of the country[25]. The shift towards the eastern region also indicated the suitable conditions along the eastern coast (Figure 3). Joshi *et al.*[47] have found that soil moisture and soil depth are the influential factors in the Himalayan region. Dominant distribution of sal was observed in alluvial soils and red loam soils in northern India, indicating the suitability of the soils due to higher water holding capacity and greater moisture content[4]. Sal species exhibits semi-evergreen habit and hence cannot survive in the drought conditions. Few sal distributions in northern Madhya Pradesh demarcated according to Champion and Seth[4] were not found in reference to field locations collected during 1999–2009; and these areas also showed lesser probability of distribution in Maxent prediction (Figures 1 and 3). This shows the non-suitability of the areas due to following reasons: (a) they are situated in the central region of India, where the disturbances due to human interference are higher and (b) they come under drier parts of the country, which could affect the growth of sal. Higher anthropogenic pressure also results in poor regeneration of sal that ultimately poses a threat to the biodiversity[5,6]. For conservation of sal in such regions, artificial regeneration should be undertaken by the authorities in collaboration with local people. A sal plantation area has been raised and maintained by local communities in conjunction with the forest department in Kharagpur, West Bengal (Figure 1 *b*). The study reveals suitability of wetter regions and moisture-rich soils for the distribution of sal. Northeastern India is one of the biodiversity hotspots and also accommodates diverse forests[48]. The shift of the sal species towards the northeastern region supports this fact and indicates the suitability of the region under increased temperatures in the future. This could be considered as one of the reasons for the conservation of the biodiversity hotspots. Though the field location data cannot be available for the future, validation using data from the last century is the most useful as it lies at the 65–80% of prediction timescale/range. An observed decrease in sal forests during 1999–2009 with respect to the 1960s calls for urgent attention. Satellite remote sensing technique proved useful in identification and characterization of sal species (as they occur in consociations and represent the top canopy) in generating past distribution scenarios, and thereby providing inputs for modelling studies leading to biological and ecological conservation implementation.

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