Predicting potential distribution, range change and niche dynamics for *Saraca asoca* (Roxb.) De Wilde: a threatened medicinal plant under climatic change

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In the Anthropocene era, understanding the impact of climate change on niche shift, species distribution, and habitat change is increasingly important for the conservation of biodiversity. In this respect, species distribution models have been considered an important tool over the last decade. The present study illustrates distributional change, niche dynamics and climatic shifts of *Saraca asoca* (Roxb.) De Wilde in India, a proven medicinal plant and a listed threatened species by IUCN, under different climate change scenarios using MaxEnt. The robustness of the model was satisfactory (AUC = 0.936), indicating a good fit. There could be a significant gain in suitable habitat between the present and future scenarios, ranging from a minimum of 52,275.17 km^2 (RCP 2.6) to a maximum of 95,994.62 km^2 (RCP 4.5). In the future, the suitable habitat range would shift towards colder regions of India, where cultivation of *S. asoca* could be taken up, thus enabling effective management of the natural habitat and population of the species. This study will help understand the effects of climate change on *S. asoca* and its implications for conservation of the species.

Keywords: Climate change, distributional changes, ecological niche models, niche overlap, *Saraca asoca*.

SARACA ASOCA (Roxb.) De. Willde (family Fabaceae, subfamily Caesalpinioideae) is an evergreen tree species with fragrant flowers and densely clustered, attractive, deep-green foliage. It is a threatened medicinal plant distributed in the tropics, predominantly occurring in Odisha, Assam, South and Central India, and in low-elevation regions (up to 750 m) of Eastern Himalaya[1]. *S. asoca* is considered a sacred plant in several Hindu scriptures as well as in the Indian Ayurvedic system. In Southeast Asian countries, *S. asoca* has been widely used to treat disorders in women, especially menorrhagia[2]. It is also used to treat a range of diseases such as uterine infections, dysentery, cancer, ulcers, menorrhagia caused by uterine fibroids, joint pain, paralysis, skin problems, etc.[3]. *S. asoca* is listed among 32 medicinal plants registered by the National Medicinal Plant Board and Planning Commission, Government of India, for research and development[4]. Despite its wide distribution, the population of this species is fragmented in several regions of the country owing to uncontrolled harvest from the wild[2,5]. Considering the threat and its economic importance, the species has been assessed as 'vulnerable' by IUCN (www.iucnredlist.org).

With the advancement of Geographic Information System (GIS) and statistical modelling, ecological theories along with these tools are being more widely used for understanding, utilizing and conserving biological resources in the face of climate change[6,7]. In recent years, species distribution models (SDMs) have become an integral tool for the assessment of the potential distribution and for predicting suitable habitats of species[8–11]. SDMs correlate occurrence and abundance data with the regional bioclimatic variables to predict future and past distributions of species[12]. The models utilize the current distribution as an input dataset, along with environmental factors associated with the species presence, to forecast the potential distribution of the target species. SDMs have become the most relevant tool for estimating and evaluating climate change impacts and species distribution[13,14].

Environmental factors, such as temperature, soil, rainfall, surface humidity, etc. significantly influence species distribution. Plant–environment interactions and their impact on plant growth have gained attention for decades by researchers[9,15]. According to IPCC, between 1880 and 2012, the average global surface temperature increased by 0.85°C; by 2100, it is expected to increase between 0.3°C and 4.8°C. Temperature and various environmental factors play a pivotal role in the synthesis of diverse plant components, particularly secondary metabolites[16]. Further, climate has become an important variable that determines the distribution and dominance of plant species and affects their growth and reproduction[17,18]. The geographical distribution

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of several medicinal plants has sharply declined in recent years. Some species have even become extinct due to lack of proper protection, the effect of global warming, and unscientific introduction and propagation[19,20]. In India, climate change threats to forest ecosystems were studied. It was observed that about 39% and 34% of the forests were under stress and may undergo changes in the A2 and B2 scenarios respectively[21]. This may lead to changes in species composition, structure and productivity of the forests in India.

In order to identify and predict suitable habitats for threatened species groups, several studies have documented significant approaches for managing and protecting these bioresources[22,23]. A number of studies are available on *S. asoca*, particularly on its population status[1], distribution[24], medicinal properties[25,26] and reproductive biology[27]. The present study focuses on the following objectives: (a) to determine the future and current distribution patterns of *S. asoca*, (b) to study the impact of climate change (future) on the distribution of *S. asoca*, (c) to emulate species migration and range dynamics, and (d) to evaluate the potential climatic niche shift of *S. asoca.*

Materials and methods

Occurrence records

The presence-only data were collected from primary and secondary resources. The primary occurrence data of the species were gathered through direct field observations, and the geographical locations were recorded using GPS (Garmin). Secondly, the occurrence data were collected from various secondary resources, viz. Global Biodiversity Information Facility (http://www.gbif.org) and herbarium records at various scientific organizations like the Botanical Survey of India; Centre for Ecological Sciences, Indian Institute of Science, Bengaluru; CSIR-Institute of Minerals and Materials Technology, Bhubaneswar, (RRL-B) and Ashoka Trust for Research in Ecology and Environment, Bengaluru (Figure 1). The coordinates were assigned to record using Google Earth and toposheets published by the Survey of India. The records obtained from secondary resources have sampling bias, which often tends to bias the niche model[28]. We reduced the bias by performing spatial thinning of occurrence records using the Sp Thin package implemented in R without reducing the niche signal at a specified distance of 10 km^2, resulting in 78 occurrence points for the environmental niche model (ENM)[29,30]. Spatial thinning is easy to execute and is an uncomplicated method to reduce data biases[28,31,32].

Environmental variables

ENM requires all the environmental variables for the prediction of species distribution. We have used 19 bioclimatic variable layers downloaded from http://www.worldclim.org and altitude (SRTM DEM) downloaded from www.earthexplorer.org[33]. The data of future climatic conditions were obtained from http://www.ccafs-data.org for all four scenarios, i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 from the global circulation model (GCM) HadGEM2-ES[34]. This model developed by the UK Met Office Hadley Centre in 2009 is widely used in constructing ENMs for various taxa[35,36]. The future bioclimatic data used in this study are according to the guidelines of the Intergovernmental Panel for Climate Change (IPCC) and recommendations of the Assessment Report 5 (AR5). The environmental variables were checked for possible correlations as they often show high colinearity, resulting in poor performance of the model, which is often misleading[37]. Hence, we selected a suite of variables for ENM of *S. asoca* using Pearson's correlation coefficient ($r^2 > 0.75$) after a pairwise comparison of all 19 environmental variables and excluded the variables that were highly correlated. The refined variables were used for building ENMs along with spatially thinned datasets. The environmental variables taken for modelling were Alt: altitude, BIO1: annual mean temperature, BIO2: mean diurnal range (mean of monthly (maximum temp – minimum temp)), BIO3: isothermality (BIO2/BIO7: temperature annual range) * (100), BIO4: temperature seasonality (standard deviation * 100), BIO5: maximum temperature of the warmest month, BIO9: mean temperature of the driest quarter, BIO12: annual precipitation, BIO14: precipitation of the

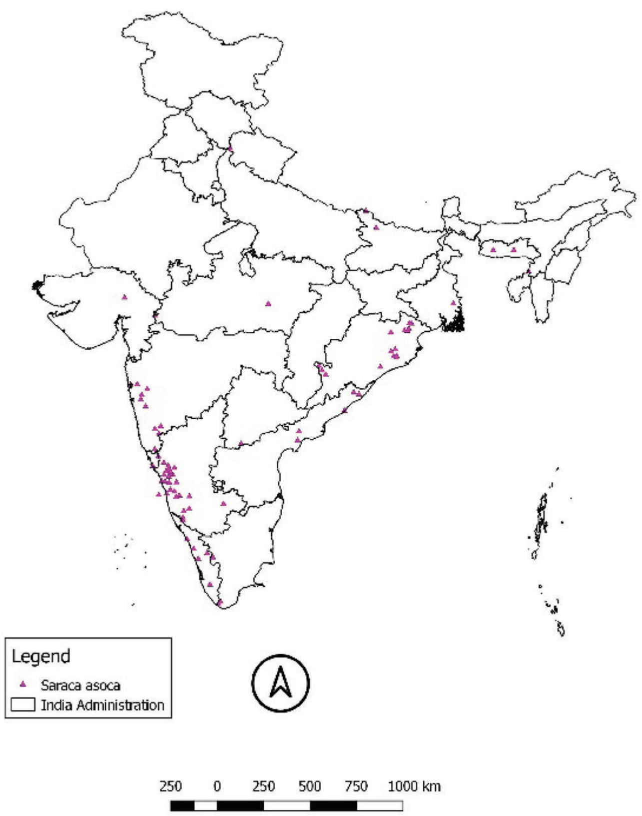


Figure 1. Distribution map of *Saraca asoca* in India used for modelling species distribution with MaxEnt.

driest month, BIO15: precipitation seasonality (coefficient of variation) and BIO18: precipitation of the warmest quarter. The environmental variables selected had a spatial resolution of 30 arcsec, often referred to as 1 km^2.

Species distribution modelling

SDMs have been successfully applied in modelling endemic species, economically important species and alien species across a wide range of taxa[14,38,39]. In the present study, the maximum entropy principle built in MaxEnt algorithm V.3.3.3k was used to predict the potential distribution of *S. asoca*[40,41]. MaxEnt estimates the probability of species distribution in the grids with suitable conditions in a given landscape by contrasting the environmental conditions of presence-only points with randomly generated 10,000 background points. We used the following settings in MaxEnt, viz. 5000 iterations, ten replicates, subsample, clog log output and auto features. The final ENMs were evaluated by randomly sub-setting 25% of occurrence records for testing using ROC (Receiver operating characteristic curve) and AUC (area under the curve) and 75% of occurrence records for model training. AUC values < 0.7 indicate worse than random, > 0.7–0.8 indicate reasonable performance, > 0.8–0.9 signify good performance, and > 0.9 indicate excellent performance[42]. Jackknife procedure was employed to calculate the relative contribution of each variable to the ENM. We modelled the potential distribution of *S. asoca* for the present and different future scenarios, i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 for 2070 (average for 2061–80). This was done to predict and compare all potential shifts in suitable habitats of the species in the future.

Distributional changes

The distributional changes and core distributional shifts were assessed for *S. asoca* according to the method of Brown[43]. The distributional changes and niche shift were assessed by converting the MaxEnt output to presence–absence (binary) maps using 10 percentile training presence threshold produced by the algorithm. The MaxEnt outputs with grids cells below the 10 percentile training presence threshold value were classified as absent, and those above the threshold as present. This information was used to calculate the distributional changes using SDMtoolbox[44]. It produces output files as .csv files (comma-separated values) with details of area change (km^2) under the following categories: –1 = range expansion; 0 = no occupancy (absence in both); 1 = no change (presence in both); 2 = range contraction and a suite of raster date for visual interpretation.

Niche overlap

The niche shifts and overlap were evaluated between the present and future conditions in India using the PCA-env method, as proposed by Broennimann *et al.*[45]. Principal component 1 (PC1) and principal component 2 (PC2) were selected and rescaled to a 100 × 100 grid cell resolution[39,45,46]. In each range, the density of occurrence points of the target species was calculated using kernel smoothing methods (using the function 'ecospat: ecospat.grid.clim.dyn'). The calculated values were then projected to the PCA surface (previously rescaled) to generate a two-dimensional surface, both for native and invasive ranges. This process ensures direct comparison between ranges by reducing sampling biases and missing data and maximising differences among environmental variables apart from any differences in range size[45,47]. The generated two-dimensional surfaces were further used to calculate the niche overlap by Schoener's D. This is useful in measuring similarity between two surfaces (for native and invasive ranges) and ranges between 0 and 1 (0: no overlap; 1: identical niche). The test for niche similarity and equivalency was done following the method of Warren *et al.*[6]. The present and future ecological niche of *S. asoca* was assessed through niche equivalency. The niche overlap value (*D*) was compared with a null distribution value obtained through 100 replicates of the dataset. When the observed *D* value was significantly lower ($P < 0.05$) than the simulated value, the hypothesis was rejected. The niche similarity test was conducted on 100 repetitions to determine the similarity of environmental niches. We used the Ecospat package implemented in R to test niche overlap[48].

Results

Model evaluation

AUC under ROC had a value of 0.9362, indicating that the MaxEnt model is a good fit. The model showed differences

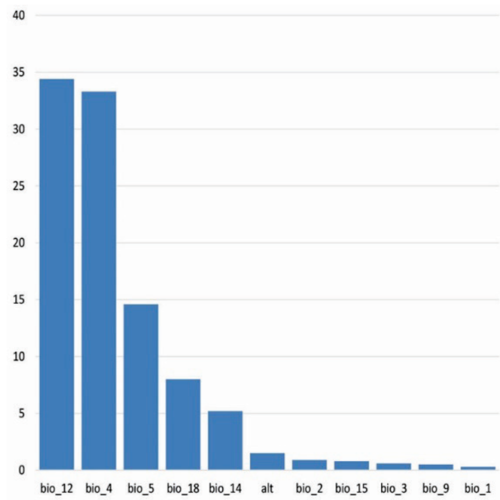


Figure 2. Percentage contribution of variables measured using jackknife. *X*-axis shows bioclimatic variables and *Y*-axis shows per cent contribution of each variable.

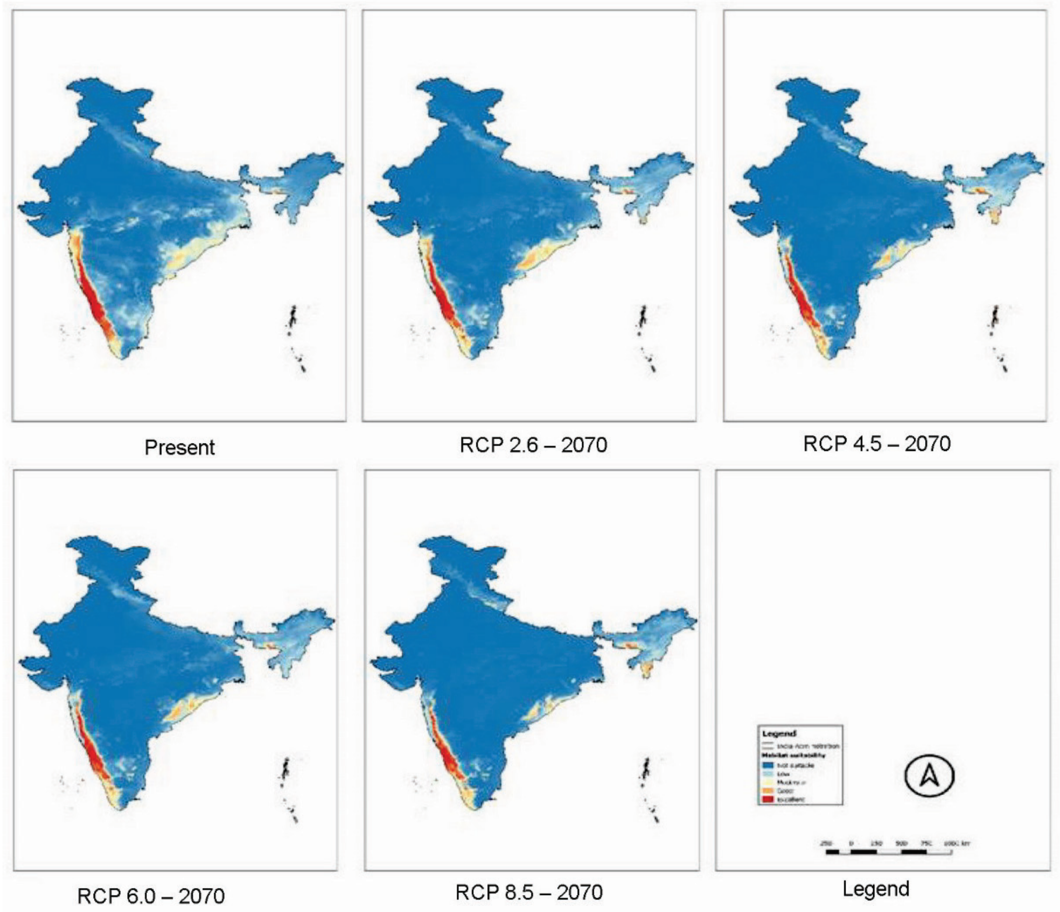


Figure 3. MaxEnt predicted potential distribution of *S. asoca* under the present and future (RCP 2.6, RCP 4.5, and RCP 6.0 and RCP 8.5) scenarios.

Table 1. Distributional changes (km^2) in *Saraca asoca* between the present and 2070

Category	Present to RCP 2.6	Present to RCP 4.5	Present to RCP 6.0	Present to RCP 8.5
Range expansion (–1)	52,275.17	95,994.62	52,458.94	64,563.70
Absence in both (0)	2,729,982.29	2,686,262.84	2,729,798.51	2,717,693.75
Presence in both (1)	317,097.95	253,621.97	263,157.03	208,676.57
Range contraction (2)	167,382.32	230,858.30	221,323.23	275,803.69

in the climate-suitable regions of the species in the present and future scenarios, indicating the possible impact of climate change over its distribution. The jackknife analysis indicated that BIO12, BIO4 and BIO5 are the top three variables contributing 34.4%, 33.3% and 14.6% respectively. The remaining variables had a 17.8% contribution in predicting the potential distribution of *S. asoca* (Figure 2).

MaxEnt predictions

In the present scenario, the possible distribution of the species was found in the Western Ghats, Deccan Peninsula, Odisha, Madhya Pradesh, Andhra Pradesh, Maharashtra, Karnataka, Tamil Nadu, Meghalaya, Mizoram and Uttrakhand. The most suitable area with optimal climatic conditions was found only in the Western Ghats. In future, across all scenarios, the high, medium and low suitable areas could be in the Western Ghats, Odisha, Meghalaya, Mizoram, Nagaland, Assam, Sikkim, West Bengal, Uttarakhand and Himachal Pradesh (Figure 3). The suitable climatic conditions for future scenarios could be similar in all cases, with the Western Ghats as the most suitable site for the species.

Distributional changes

The distributional change analysis revealed that there would be slight expansion between the present and future scenarios,

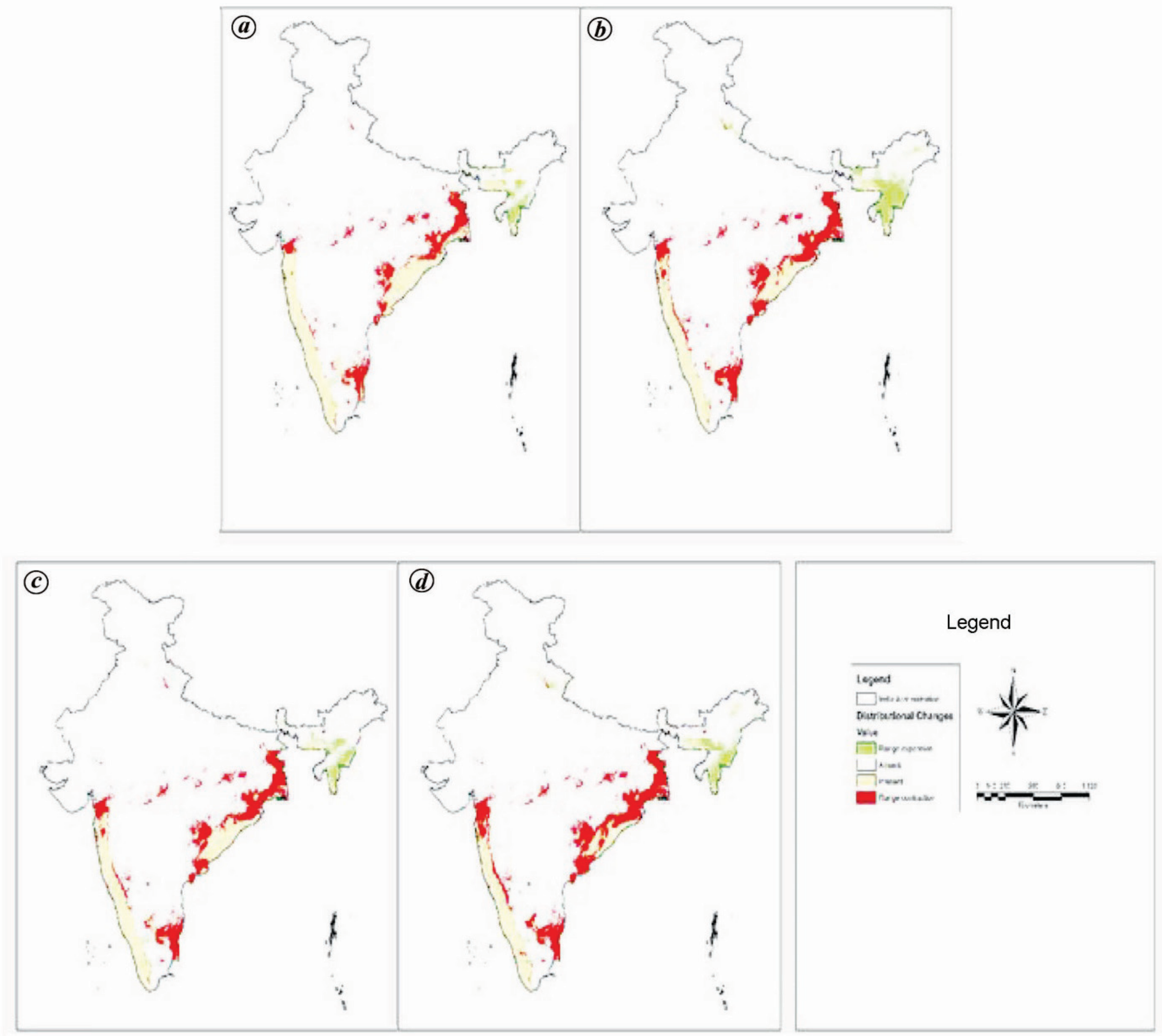


Figure 4. Distributional changes – Present versus (***a***) RCP 2.6, (***b***) RCP 4.5, (***c***) RCP 6.0 and (***d***) RCP 8.5. Range expansion (–1, green colour), no occupancy in the present and future scenarios (0, white colour), no change, present in both scenarios (1, yellow colour) and range contraction (2, red colour).

ranging from 52,275.17 km^2 (RCP 2.6 – 2070) to 95,994.62 km^2 (RCP 4.5 – 2070). Further, the studied species suffered from a significant loss in habitat range due to climate change by 167,382.32, 230,858.30, 221,323.23 and 275,803.69 km^2 in the case of RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 respectively (Table 1 and Figure 4).

The distributional change analysis between the present and future scenarios (all scenarios, 2070) revealed that the Western Ghats and parts of coastal Odisha would remain prominent hotspots for *S. asoca*. It will lose its niche in central parts of India, including Madhya Pradesh, Chhattisgarh and Jharkhand, due to the impact of climate change from the present to future scenarios. However, the significant niche expansion has been predicted in Meghalaya, Assam, Tripura, Manipur and Nagaland towards Eastern Himalaya, followed by the colder climatic areas bordering Himachal Pradesh and Uttarakhand (Figure 4).

Evaluation of niche properties

In the future, a niche overlap of 86.08% (Schoener's D = 0.860), 78.65% (Schoener's D = 0.786), 80.12% (Schoener's D = 0.801), and 69.23% (Schoener's D = 0.692) have been predicted in RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 in 2070 respectively. In general, there was a maximum overlap of 86.08% in the case of RCP 2.6 – 2070 (Table 2 and Figure 5).

Under scenario RCP 2.6, variation in climatic conditions was 44.13% and 26.89% along PC1 and PC2 respectively. Compared to scenario RCP 4.5, the variation was 43.20% and 27.50% along PC1 and PC2 respectively. In the case of RCP 6.0, the variation was 43.73% and 26.39% along PC1 and PC2 respectively. Lastly, in RCP 8.5 – 2070, the variation observed was 42.63% and 26.51% along PC1 and PC2 respectively.

Table 2. Results of *S. asoca* niche overlap analysis with Ecospat

Niche comparison pairs	PC1 (%)	PC2 (%)	Schoener's *D*	Similarity (*P*-value)	Equivalency (*P*-value)
Present – RCP 2.6	44.13	26.89	0.860	0.009	0.009
Present – RCP 4.5	43.20	27.50	0.786	0.009	0.009
Present – RCP 6.0	43.73	26.39	0.801	0.009	0.009
Present – RCP 8.5	42.63	26.51	0.692	0.009	0.009

Niche similarity and equivalency

In the pairwise comparisons between present and future scenarios, the null hypothesis was consistently rejected for both niche equivalency and niche similarity ($P < 0.05$). This suggests that the adaptation process of *S. asoca* is expected to maintain identical niches across the future scenarios.

Discussion and conclusion

Climate change is a crucial problem across the globe. Due to climate change, various flora and fauna are under severe threat. While some species might face extinction from natural habitats, others may have to adapt to new climatic conditions as current habitats would be unsuitable in the future[49]. Therefore, information on species distribution and drivers of the distribution under climate change is important for effectively reintroducing and utilising a species in a given landscape[50]. SDMs have been successfully used for addressing the pressing conservation concerns[38], mapping invasive risk[14,51] and disease monitoring[52] due to anthropogenic pressure and climate change[53].

Previous studies on endemic tree species of India using MaxEnt indicate that the species tend to shift in the north-eastern direction due to climate change. It has also been observed that moisture plays a key role in such a shift towards northern and eastern India with more certainty, which agrees with the present study[54–56]. The temperature seasonality and maximum temperature of the warmest month were the other significant factors influencing the distribution of the species, in addition to annual precipitation. These factors have also been shown to influence species adaption and distribution in numerous studies[57].

Our analysis revealed that *S. asoca* was able to colonize or spread across South India, including the Western Ghats, Andhra Pradesh, Tamil Nadu, Odisha, Madhya Pradesh, Meghalaya, Mizoram and Uttarakhand due to cold climatic conditions. This reveals that *S. asoca* is adapting towards colder climatic conditions (Figure 5). The jackknife analysis also indicated that annual precipitation, temperature seasonality and maximum temperature of the warmest month were the predominant variables driving the potential distribution of *S. asoca*.

According to an IPCC report[58], the temperature will become warmer by 1.0°–3.0°C by 2070 (RCP 2.6–RCP 8.5). Therefore, *S. asoca* would suffer habitat loss in those areas where the temperature would likely increase and colonize areas having colder climate, which is towards colder regions like Mizoram, Meghalaya, Assam, Uttarakhand and Himachal Pradesh. Further, this is evidenced by the niche shift analysis. In this study, *S. asoca* was found to shift towards the high-moisture regions in North East India and coastal areas of Odisha, or more precisely, towards the high-altitude regions.

Other studies in India using the maximum entropy approach have reported that due to climate change, many regions that are suitable in the present climatic conditions will become unsuitable, while certain areas will become suitable in the future[39]. The spatial delineation of habitat change in the present study indicates that there is significant niche expansion in the Western Ghats, Meghalaya, Assam, Tripura, Manipur and Nagaland towards Eastern Himalaya, followed by the colder climatic areas bordering Himachal Pradesh and Uttarakhand. The potential increase in area includes 52,275.17 (RCP 2.6 – 2070) to 95,994.62 km^2. On the other hand, there is potential contraction of the climatically suitable areas by 167,382.32 to 275,803.69 km^2.

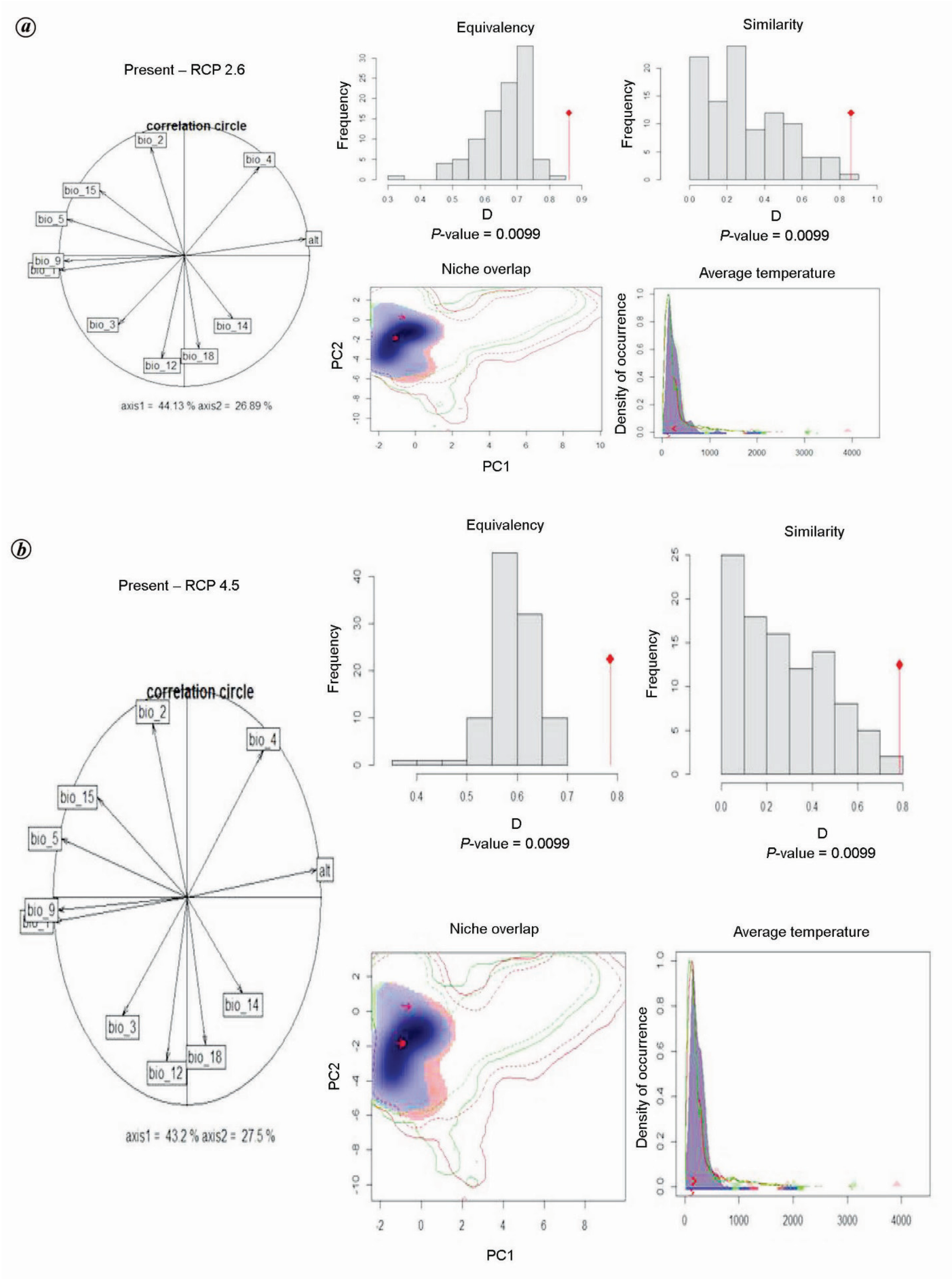
Niche overlap, equivalency and similarity

In the present study, we compared the niche shift in *S. asoca*. The PCA-env analysis showed a moderate variation of 26.39–44.13% between the present and future scenarios, indicating that the rest of the niche will be shifted from the original habitat of the species. The niche overlap results showed a maximum overlap of 86.08% in RCP 2.6 – 2070, indicating a significant loss in the climatic niche for *S. asoca*.

We also analysed the niche similarity and niche equivalency, which highlighted that the environmental niche is not similar or identical for the species under the present and future climatic conditions. On the other hand, tests also confirmed that the species have increased environmental niche space at present and in the future than randomly expected. It was also evident that there was a similarity of niche for the species in the present and future scenarios, but not the environmental conditions[6,39].

Conservation implications

Assessing the effects of climate change on the distribution of species using SDM is vital in developing effective conservation and long-term management of the species[19,59,60].



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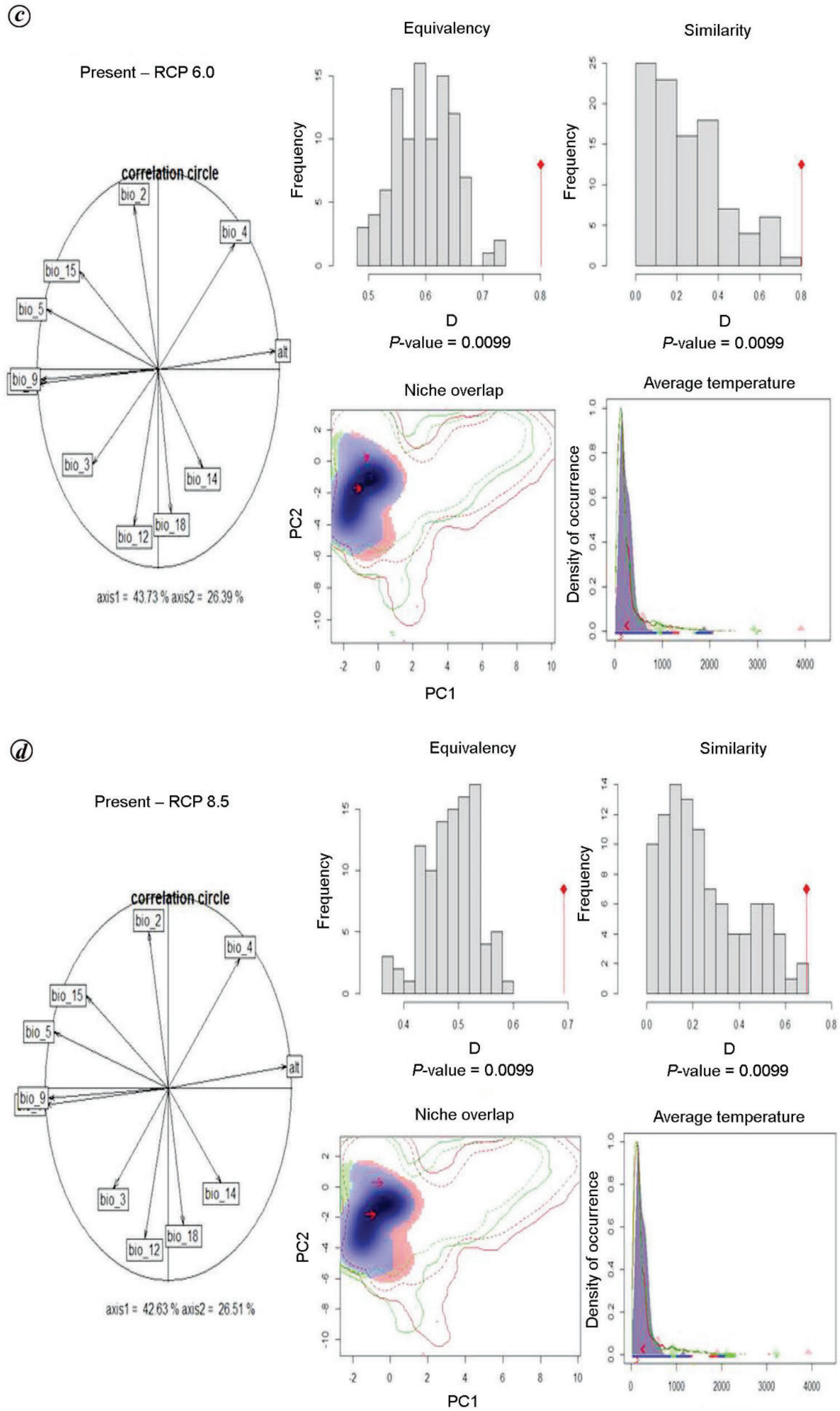

Figure 5 *a–d*. Niche overlap analysis using Ecospat. The correlation circle shows variation in climatic conditions on PC1 and PC2 (PCA-env analyses). The blue and red colours represent density of species occurrence in the present and future scenario respectively. Bar plots represent niche similarity and niche equivalency between the present and future scenarios. Red arrows indicate shift.

The spatial delineation of range increase and/or decrease indicates that *S. asoca* will suffer a significant loss in the habitat in future across all scenarios (RCP 2.6 –RCP 8.5, 2070), followed by a small gain in suitable habitats (newer areas) across all scenarios (RCP 2.6 – RCP 8.5, 2070) by 52,275.17–95,994.62 km^2. Further, the gain in habitat is towards the colder parts of Meghalaya, Mizoram, Assam, Uttarakhand and Himachal Pradesh. Therefore, while developing effective plans for the conservation and cultivation of this species, due care must be taken for *in situ* conservation and identifying suitable areas for cultivation. Secondly, while developing management policies, factors like livelihood options for local people, land-use change and climatic patterns should be given due consideration.

MaxEnt species distribution modelling is an important tool for threatened species[61]. Although this study only employed MaxEnt prediction, examining additional machine-learning techniques could improve the interpretation. Further, the lower number of occurrence points, including the collection procedure may result in model bias. The model provides an insight to the predicted distribution of *S. asoca* in the present and future scenarios.

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