

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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Abstract

In this Anthropocene era, understanding the impact of climate change on niche shift, species distribution and habitat change is increasingly important for conservation of biodiversity. In this respect, species distribution models (SDMs) have been considered as an important tool over last decade. This study illustrated distributional change, niche dynamics and distributional 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 present and future ranging from minimum 52,275.17 km² (RCP 2.6) to maximum 95,994.62 km² (RCP 4.5). In future, the suitable habitat range would be shifted towards colder regions of India, where cultivation of *S. asoca* could be taken up thus enabling effectively management of the natural habitat and population of the species. This study will be helpful in understanding the climate change effects on *S. asoca* and its implications for conservation of the species.

Key Words: *Saraca asoca*, Ecological Niche Models; Climate change; Distributional changes; Niche Overlap

Introduction

Saraca asoca (Roxb.) De. Willde (Family Fabaceae; Sub family: 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. The plant is predominantly occurs in Odisha, Southern India, Assam, Central India, and in low elevation regions (up to 750 m) in the Eastern Himalayas¹. *S. asoca* is as a sacred plant and medicinally important tree in several Hindu scriptures as well as in Indian Ayurvedic system. In South-East Asian countries, *S. asoca* has been widely used in the treatment of several feminine disorders especially in menorrhagia². It is also used in the treatment of a range of diseases such as uterine infections, dysentery, cancer, ulcers, menorrhagia especially caused for uterine fibroids, joint pains, paralysis, skin problems etc³. *S. asoca* is listed among 32 medicinal plants registered by National Medicinal Plant Board and Planning Commission of Government of India for research and development purpose⁴. Despite its wide distribution, the population of the species is fragmented in several regions of the country owing to uncontrolled harvest from wild populations^{2,5}. Considering the threat and its economic importance, it 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 becoming more widely in use for understanding, utilizing and conserving the biological resources in the face of climate change^{6,7}. In recent years, species distribution models (SDMs) have become an integral medium of assessment for potential distribution and for predicting suitable habitats of species⁸⁻¹¹. SDMs are the tool that correlate occurrence and abundance data with the regional bioclimatic variables to predict future and past distributions of species¹². The models predict current distribution as input data set along with environmental correlates where species occurs

and predict potential distribution of target species. SDMs have become the most relevant tool for the estimation and evaluation of climate change impacts and species distribution^{13,14}.

There are remarkable influences of environmental factors, such as temperature, soil, rainfall, surface humidity etc. on species distribution. Plant-environment interactions and their impact on plant growth has been a centre of attention for decades by researchers^{9,15}. According to IPCC (2014), between 1880 and 2012, the average global surface temperature increased by 0.85°C, and by 2100, that temperature is expected to rise between 0.3°C to 4.8°C. Temperature and other environmental factors play a crucial role in synthesis of different ingredients of plants, especially of medicinal plants¹⁶. Further, climate has become an important variable that determines the distribution and dominance of plant species as well and affects their growth and reproduction^{17,18}. The geographical distribution of a number of medicinal plant species has sharply declined in recent years and some species have even gone extinct due to the lack of efficacious protection, effect of global warming and unscientific introduction and propagation^{19,20}. In India, climate change threats on forests ecosystems were studied and found that about 39% and 34% of the forests are under stress that may undergo change at A2 and B2 scenario respectively²¹. It may lead to changes in species composition, structure and productivity of the forests in India.

In this regard, in order to identify and predict the suitable habitats for threatened species groups, several studies have documented significant approaches for the management and protection of these bio-resources^{22,23}. There are several studies available on *S. asoca*, particularly on population status¹, distribution²⁴, medicinal properties^{25,26}, and reproductive biology²⁷. The present study focused 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 finally, 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 observation and the geographical locations were recorded using GPS (Garmin). Secondly, the occurrence data were collected from various secondary resources which were; Global Biodiversity Information Facility (GBIF, <http://www.gbif.org>) and herbarium records at various scientific organizations viz., Botanical Survey of India (BSI); Centre for Ecological sciences (CES), IISC, Bangalore; CSIR-IMMT, Bhubaneswar (RRL-B) and Ashoka Trust for Research in Ecology and Environment (ATREE), Bangalore (Figure 1). The coordinates were assigned to record using Google earth and Topo-sheets published from Survey of India. The records obtained from secondary resources have sampling bias, which often tend to bias the niche model²⁸. We reduced the bias by performing spatial thinning of occurrence records by using Sp Thin package implemented in R without reducing the signal of niche at specified distance of 10 km² resulting in 78 occurrence points for Environmental Niche Model (ENM)^{29,30}. The spatial thinning is easy to execute and is an uncomplicated method to reduce the biasness of data^{28,31,32}.

Environmental Variables

ENM requires all the environmental variables for 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.org³³. 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 Global Circulation model (GCM) Hadgem2-ES³⁴. The Hadgem2-ES was developed by UK Met Office Hadley Centre in 2009 which is widely used in constructing ENM's for various taxa^{35,36}. The future bioclimatic data used in this study is as

per the guidelines of Intergovernmental Panel for Climate Change (IPCC) and recommendations of Assessment report 5 (AR5). The environmental variables were checked for possible correlations as they often show high co-linearity resulting in poor performance of the model, which often mislead³⁷. Hence, we selected a suite of variables for ENM of *S. asoca* using Pearson's correlation coefficient ($r^2 > 0.75$) after pair wise comparison of all nineteen environmental variables and excluded the variables that are highly correlated. The refined variables were used for building ENM's 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 (max temp - min temp), BIO3: Isothermality (BIO2/BIO7) *(100), BIO4: Temperature Seasonality (standard deviation *100, BIO5: Max Temperature of Warmest Month , BIO9: Mean Temperature of Driest Quarter, BIO12: Annual Precipitation, BIO14: Precipitation of Driest Month, BIO15: Precipitation Seasonality (Coefficient of Variation) and BIO18: Precipitation of Warmest Quarter. The environmental variables selected had a spatial resolution of 30 Arc Seconds often referred to as 1 sq. km.

Species Distribution Modelling (SDM)

SDMs are successfully applied in modelling of endemic species, economically important species, alien species across wide range of taxa^{14, 38, 39}. In this study, 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 following settings in MaxEnt viz., 5,000 iterations, 10 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 curve)

and 75% of occurrence records for model training. The AUC values < 0.7 indicates worse than random, $> 0.7 - 0.8$ indicates reasonable performance, $> 0.8 - 0.9$ signifies good performance and whilst, $AUC > 0.9$ indicates excellent performance⁴². Jackknife procedure was selected to calculate the relative contribution of each variable to the ENM. We modelled potential distribution of *S. asoca* for present and for different future scenarios i.e. RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 for 2070 (average for 2061-2080). This was to predict and compare all potential shifts in suitable habitat of the species in future.

Distributional Changes

The distributional changes and core distributional shifts were assessed for *S. asoca* according to the method of Brown (2014)⁴³. The distributional changes and niche shift were assessed by converting the MaxEnt output to presence-absence (binary) maps by using 10 percentile training presence threshold produced by MaxEnt algorithm. The MaxEnt outputs having grids cells below the 10 percentile training presence threshold value were classified as absent and above the threshold was classified as present. This information was used to calculate the distributional changes using SDM Toolbox⁴⁴. The SDM Toolbox produces output files in .csv files (comma separated values) with details of area change in km² with following categories: -1 = range expansion; 0= no occupancy (absence in both); 1 = no change (presence in both); 2 = range contraction and suite of raster for visual interpretation.

Niche Overlap

The niche shifts and overlap were evaluated between present and future conditions in India using PCA-env method as proposed by Broennimann et al., (2012)⁴⁵. The PC1 and PC2 were taken 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 by using kernel smoothing methods (using the function 'ecospat: ecospat.grid.clim.dyn'). The calculated values were then

projected to PCA surface (previously rescaled) for generation of two-dimensional surface both for native and invasive ranges. This process is virtuous that ensures direct comparison between ranges by reduction of sampling biasness and missing data, and also through maximizing differences among environmental variables apart of any differences in range size^{45,47}. The generated two-dimensional surfaces were further used to calculate the niche overlap by Schoener's D. Schoener's D is useful in measurement of similarity between two surfaces (for native and invasive ranges) that ranges between 0-1 (0: no overlap; 1: identical niche). The test for niche similarity and equivalency was done following the method given by Warren (2008)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 dataset. When the observed 'D' value was found significantly lower ($p < 0.05$) than the simulated value, the hypothesis was rejected. The niche similarity test was conducted on 100 repetitions to address the similarity of environmental niches. We used Ecospat package implemented in R to test niche overlap⁴⁸.

Results

Model evaluation

The Area Under Curve (AUC) under Receiver operating characteristic curve (ROC) had a value of 0.9362 indicating that MaxEnt model is a good fit. The model showed differences in the climate suitable regions of the species in present and future indicating possible impact of climate change over its distribution. The jackknife analysis of variable contribution indicated that Bio 12, Bio 4 and Bio 5 are the top three variables contributing at 34.4%, 33.3% and 14.6%, respectively. The remaining variables had 17.8% contribution in predicting potential distribution of *S. asoca* (Fig 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 Uttarakhand. The highest 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 condition for future scenarios could be similar in all cases with the Western Ghats as most suitable site for the species.

Distributional changes

The distributional change analysis revealed that there would be slight expansion between present and future scenario ranging from 52,275.17 km² (RCP 2.6 – 2070) to 95,994.62 km² (RCP 4.5 – 2070). Further, the studied species suffers from significant loss in habitat range due to climate change by 1,67382.32 km², 2,30,858.30 km², 2,21,323.23 km² and 2,75,803.69 km² in case of RCP 2.6, 4.5, 6.0 and 8.5, respectively (Table 1 and Figure 4).

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

Evaluation of niche properties

In future, the 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 $D = 0.692$) is found in RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 in 2070, respectively. In general, there was maximum overlap of 86.08% in case of RCP 2.6 – 2070 (Table 2 and Figure 5).

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

Niche similarity and equivalency

In the pair wise comparisons between present versus future, the null hypotheses was rejected in all the scenarios for niche equivalency and for niche similarity ($P < 0.05$), thereby indicating that the process of adaptation of *S. asoca* is in identical niches across future. Further, niche overlap tests indicated that *S. asoca* tends to adopt towards cold climatic conditions which is evident through the shift in niche centroid across all the scenarios (Table 2 and Figure 5).

Discussion

Climate change is one of the pressing issues across the globe. Due to climate change, various floras and faunas are under severe threat while some species might face extinction from natural habitats (World Bank, 2008) and some species shift to adapt new climatic conditions as current habitats would be unsuitable in future⁴⁹. Therefore, information on species distributions and the drivers of the distribution under climate change is key for effective

reintroduction and utilization of a species in a given landscape⁵⁰. SDMs have been successfully applied for addressing the pressing conservation concerns³⁸, mapping invasive risk^{14,51} and disease monitoring⁵² due to anthropogenic pressures and climate change⁵³.

Previous studies on endemic trees species of India using MaxEnt indicate that species tend to shift in the north-east direction in India due to climate change. It has also been noted that moisture plays a key role or influence in the distribution to shift towards northern and eastern India with higher amount of certainty, which is in agreement with our study^{54,55,56}. The temperature seasonality and the 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 across numerous studies⁵⁷.

Our analysis revealed that *S. asoca* was able to colonize or spread across the South India including Western Ghats, Andhra Pradesh, Tamil Nadu, Odisha, Madhya Pradesh, Meghalaya, Mizoram, and Uttarakhand due to cold climatic conditions (Figure 2). This indicates that *S. asoca* was adopting towards colder climatic conditions (Figure 5). The jackknife analysis too indicates that Annual precipitation, Temperature seasonality and maximum temperature of the warmest month were the predominant variables driving the potential distribution of *S. asoca* (Figure 3).

As per IPCC fifth assessment report (IPCC, 2014)⁵⁸, the temperature would become warmer by 1.0°C – 3.0°C by 2070 (RCP2.6 – RCP 8.5). Therefore, *S. asoca* would suffer habitat loss in those areas where temperature would likely to raise and colonize in the areas of colder climate conditions, which is towards colder regions such as 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 places in North

East India and coastal areas of Odisha or in other words more precisely towards the high altitudinal regions (Figure 4 and 5).

Other studies in India using the maximum entropy approach have noted that due climate change, many regions that are suitable in the present climatic conditions will become unsuitable while certain areas becomes suitable in future³⁹. The spatial delineation of the habitat change in this study indicates that there is a significant expansion of the niche in Western Ghats, Meghalaya, Assam, Tripura, Manipur and Nagaland towards Eastern Himalayas followed by the colder climatic areas bordering Himachal Pradesh and Uttarakhand (Figure 4). The potential increase in the area includes 52,275.17 km² (RCP 2.6 -2070) to 95,994.62 km² and on the other hand, there is potential contraction of the climatically suitable areas by 1, 67,382.32 km² to 2, 75,803.69 km² (Table 1 and Figure 4)

Niche overlap, equivalency and similarity

The present study compared the niche shift in *S. asoca*. The PCA-env analysis showed that there was moderate amount of variation of 26.39% to 44.13% between present and future indicates that the rest of the niche will be shifted from the original habitat of the species. The niche overlap results showed that there was maximum overlap of 86.08% in case of RCP 2.6 – 2070, which indicates a significant loss in climatic niche for *S. asoca* (Table 1 and Figure 5).

This study also analyzed the niche similarity and niche equivalency which highlighted clearly that the environmental niche are not similar or exactly identical for the species under present and future climatic conditions. On the other hand, tests also confirmed that the species have the increased environmental niche space at present and in future than randomly expected. It was also evident that there was a similarity of niche for the species in present and future but not the environmental conditions^{6,39} (Figure 5).

Conservation implications

Assessing the effects of climate change on the distribution of the species using SDM is vital in developing effective conservation and long-term management of the species^{19,59,60}. The spatial delineation of range increase and/or decrease indicates that *S. asoca* suffers significant loss in the current habitat in future across all scenarios (RCP 2.6 - RCP 8.5 - 2070) followed by a small gain in suitable habitats (newer areas) in all scenarios (RCP 2.6 - RCP 8.5, 2070) by 52,275.17 - 95,994.62 km². Further, the gain in the habitat is towards the colder parts of the Meghalaya, Mizoram, Assam, Uttarakhand and Himachal Pradesh. Therefore, while developing the effective plans for identifying conservation and cultivation of this species, a due care should be given for *in-situ* conservation and identifying suitable areas for cultivation. Secondly, while developing the management policy, the factors like livelihood options for local people, land use change and climatic patterns should be given due consideration.

MaxEnt species distribution modeling is an important tool for threatened species⁶¹ (Gebrewahid et al. 2020). 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 make the model biased. Moreover, the model provides an insight to the predicted distribution of *S. asoca* in present and future.

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Table 1: Distributional changes (km²) in *S. asoca* between Present to 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) | 27,29,982.29 | 26,86,262.84 | 27,29,798.51 | 27,17,693.75 |
| Presence in both (1) | 3,17,097.95 | 2,53,621.97 | 2,63,157.03 | 2,08,676.57 |
| Range contraction (2) | 1,67,382.32 | 2,30,858.30 | 2,21,323.23 | 2,75,803.69 |

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

| Niche comparison pairs | PC1(%)) | PC2(%) | Schoener's D | Similarity (p value) | Equivalenc y (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 |

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

Figure 2: Percentage contribution of variables measured using jackknife. X-axis shows bioclimatic variables and Y-axis shows percent contribution of each variables

Figure 3: MaxEnt predicted potential distribution of *S. asoca* under Present and Future (RCP 2.6, RCP 4.5, and RCP 6.0 and RCP 8.5).

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 present and future scenario (0, white colour), no change, present in both scenarios (1, yellow colour) and range contraction (2, red colour)

Figure 5 (A-D): Niche Overlap analysis using Ecospat. The correlation circle shows the variation in climatic conditions on PC1 and PC2 (PCA-env analyses). The blue and red shadings represent density of species occurrences in current and future scenario respectively. The bar plots represent niche similarity and niche equivalency between present and future scenarios. The bold Red arrows indicates shift. Left to Right – Correlation circle, Niche Equivalency, Niche Similarity, Niche overlap and Shift across Temperature change.

Figure 1:

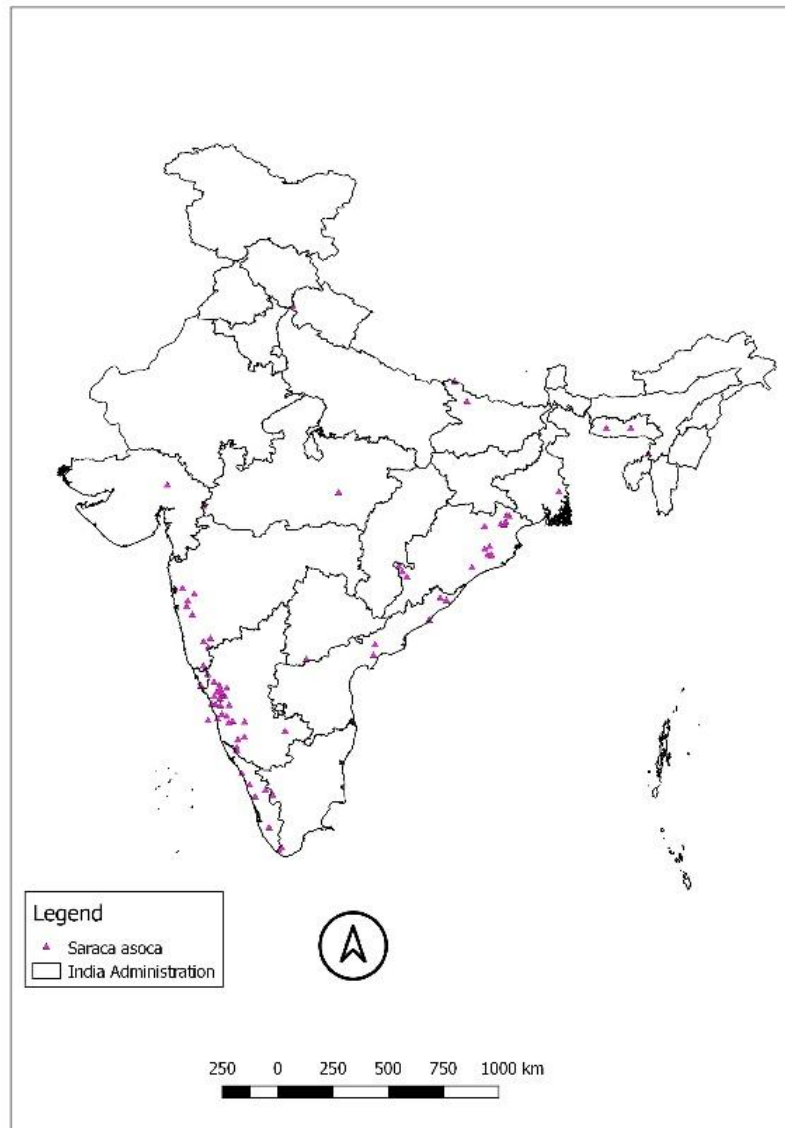


Figure 2:

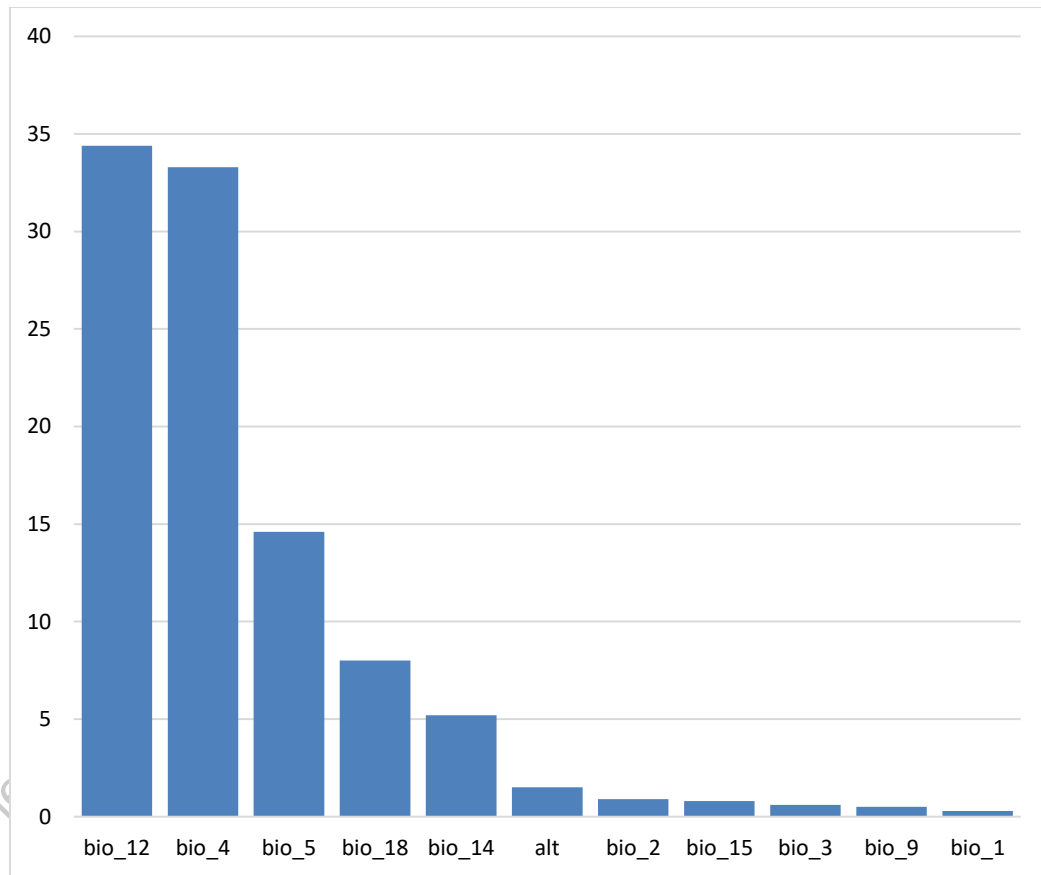


Figure 3:

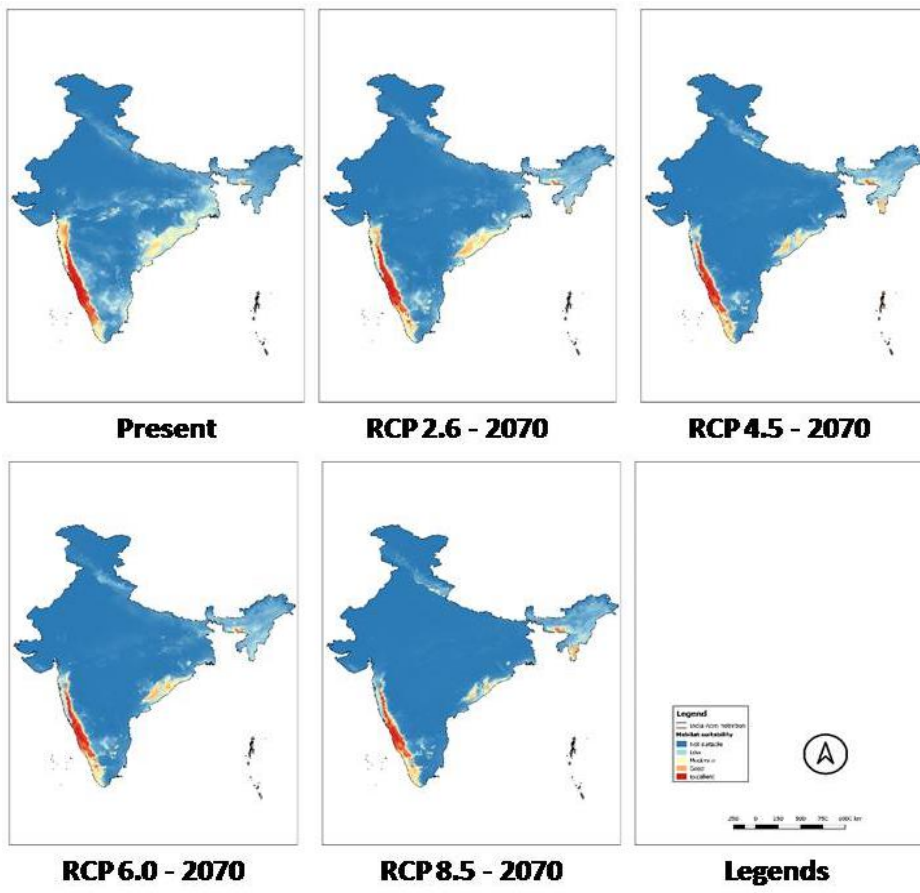


Figure 4:

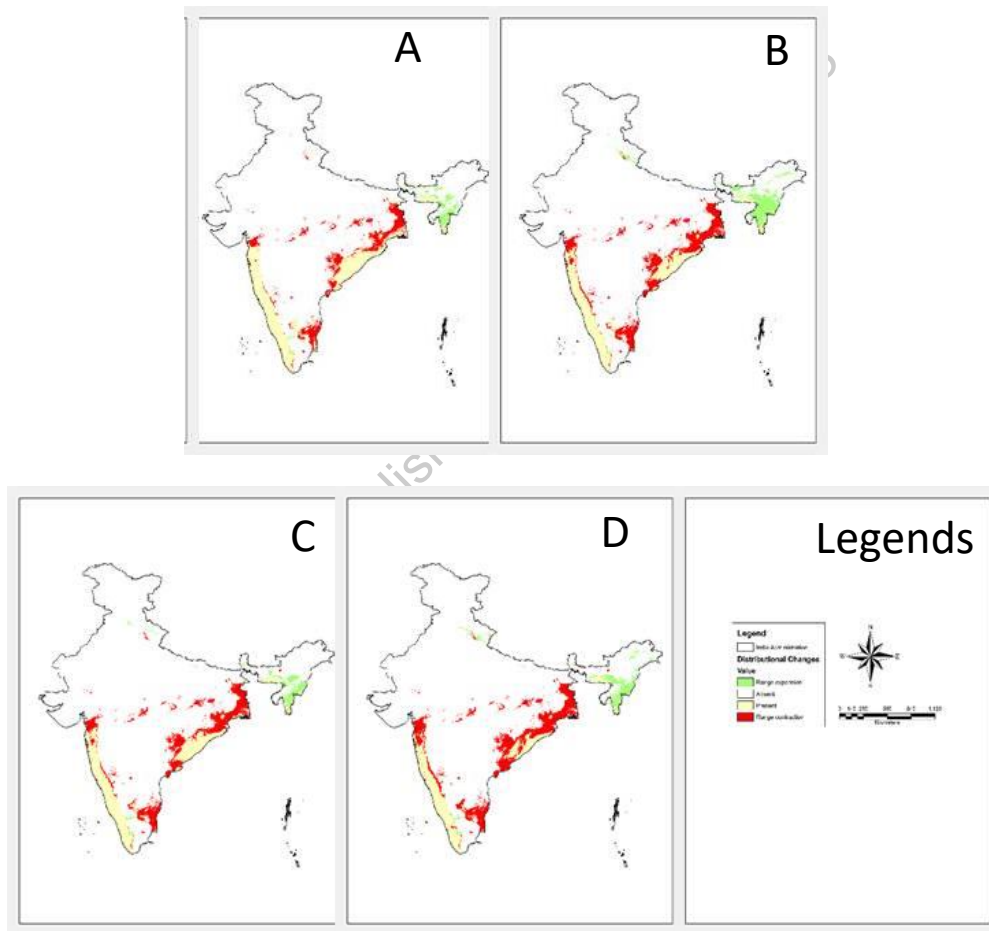


Figure 5 A.

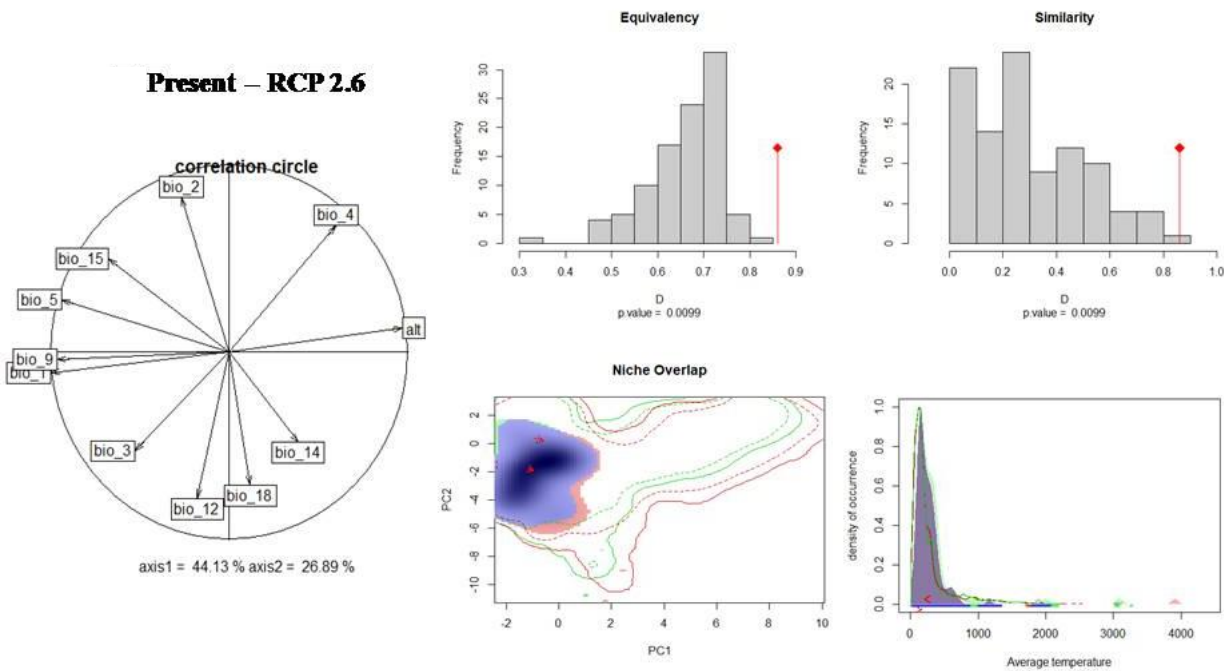
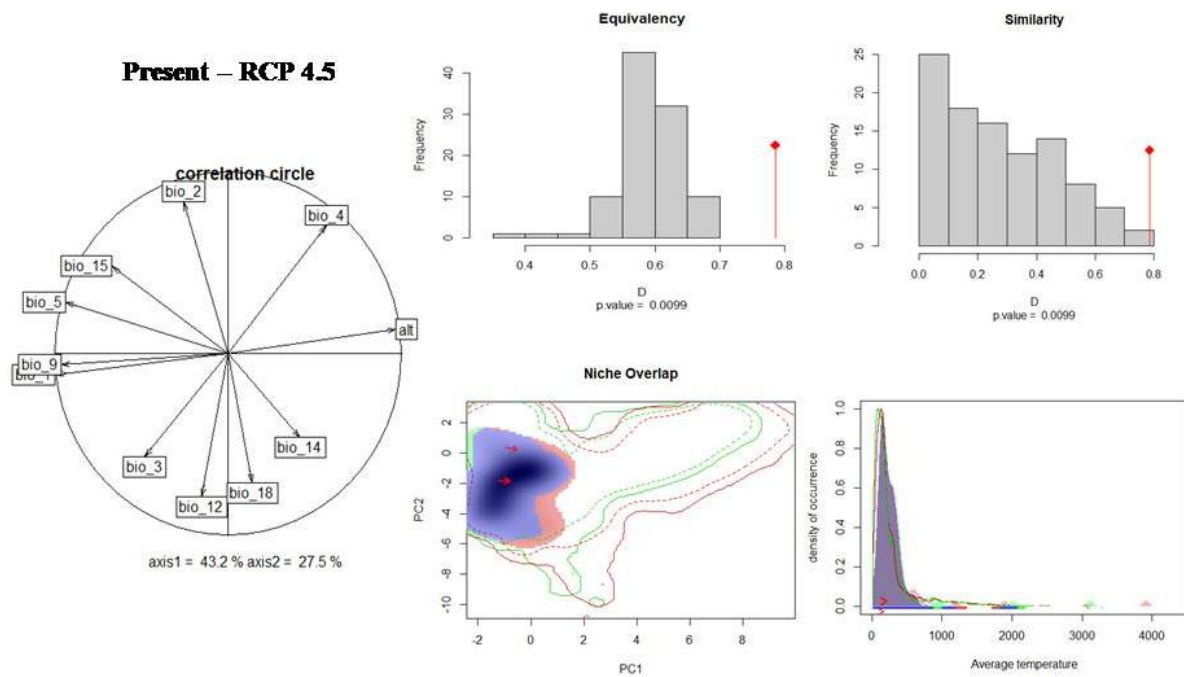


Figure 5 B.



Unedited

Figure 5 C.

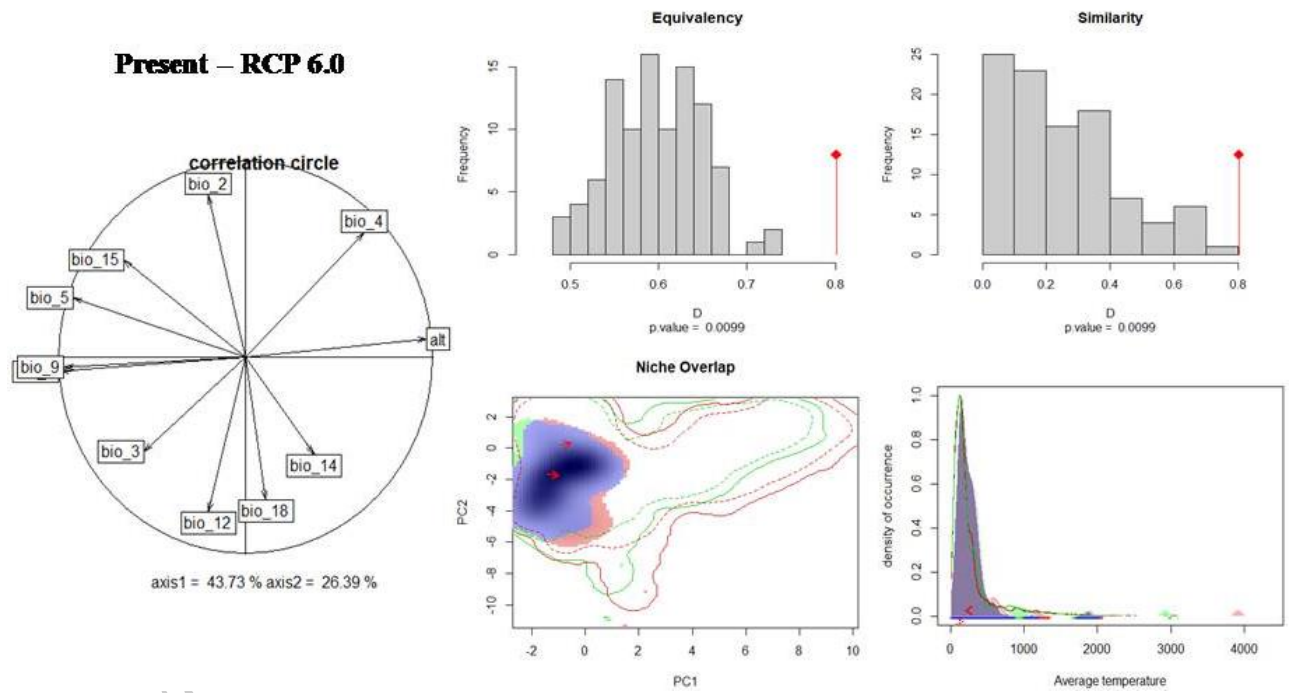


Figure 5 D.

