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HABITAT SUITABILITY MODELLING FOR CONSERVATION OF *HABENARIA DIPHYLLA* (NIMMO) DALZELL: MEDICINAL ORCHID IN WESTERN GHATS OF KERALA (INDIA) UNDER DIFFERENT CLIMATIC SCENARIOS

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Abstract

Habenaria diphylla (Nimmo) Dalzell, is a tuberous geophytic orchid that thrives in wet tropical biomes and grassy hill slopes. Presently, a Maximum Entropy (MaxEnt) Modelling approach was used to estimate the potential distribution of *Habenaria diphylla* in Kerala, India, considering both present and future climatic scenarios. The MaxEnt model predicted habitat suitability for *H. diphylla* with an area of approximately 1344 km², showing high probability zones concentrated in the Northern parts of Kerala and it was revealed that Bio17 (precipitation of driest quarter), Bio12 (annual precipitation), solar radiation (March), and Topographic Position Index (TPI) were the most significant predictor variables influencing distribution of *H. diphylla*. Habitat suitability for *H. diphylla* was projected under future climate scenarios (2020-2100) using Shared Socioeconomic Pathways (SSPs) 126, 245, 370, and 585. Under SSP370 and SSP585, highly suitable areas for *H. diphylla* decreased by 73.2% and 0.35% respectively by 2080-2100, due probably to an increase in temperature and declining rainfall.

Introduction

HABENARIA WILLD., contains about 898 species spread across tropical and subtropical regions of the old and new worlds and it is the largest genus of terrestrial orchids (Govaerts, 2015; POWO, 2024). *Habenaria diphylla* (Nimmo) Dalzell, commonly known as *Two-leaved Habenaria*, is a tuberous geophytic orchid that thrives in wet tropical biomes and grassy hill slopes. The plant produces several loosely or heavily flowered racemes, with oblong-lanceolate petals measuring 3.5 to 6 mm (Van *et al.,* 2021). Flowering occurs from July to October and it is listed as *Not Evaluated* on the IUCN Red List (Gaikwad *et al.,* 2015).

Species distribution models predict potential species ranges using ecology, geography, and limited distribution data (Franklin, 2013). Ecological Niche Modelling (ENM) utilize statistical, machine learning, and spatial analysis techniques to quantify species-environment relationships, characterizing niche dimensions and boundaries (Barbosa *et al.,* 2012; Jalal and Singh, 2017). By understanding the complex interactions between species and their environment, ENMs informs conservation strategies, climate change impact and biodiversity management (Chefaoui *et al.,* 2015). Currently, various geo-statistical models and tools are employed to simulate the global distribution of plant species, assess spatial patterns of species diversity, and evaluate the impacts of climate change (Kumar and Stohlgren, 2009; Saran *et al.,* 2010) and among these models, the maximum entropy (MaxEnt) model has emerged as the most dependable choice for species distribution Modelling. Maximum Entropy (MaxEnt) is a programme that employs a machine learning algorithm rooted in the principles of maximum entropy to model the distribution range and suitable habitats of plant species using presence data (Jaynes, 1957; Shilky *et al.,* 2023). The MaxEnt model [Maxent (amnh.org)] provides a probability estimate for species presence, ranging from 0 (lowest probability) to 1 (highest probability).

The Shared Socioeconomic Pathways (SSPs) show how societal, economic, and land-use changes affect local climates and scenarios also represent varying levels of challenges to climate change mitigation and adaptation (Kebede *et al.,* 2018). Each SSP provides quantitative data derived from socio-economic, demographic, and integrated assessment models, offering projections of future socioeconomic growth (O'Neill *et al.,* 2014). SSP1 represents a sustainability pathway with low challenges for both mitigation and adaptation. SSP2, the middle of the road scenario, involves intermediate challenges for both. SSP3 reflects a fragmented world with high challenges for both mitigation and adaptation. SSP4 highlights inequality, characterized by high adaptation challenges

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and low mitigation challenges, while SSP5 depicts a fossil-fuel-driven future with high reliance on conventional energy sources (Kebede *et al.,* 2018). The present study aimed to examine the habitat suitability Modelling of *Habenaria diphylla* in the Western Ghats of Kerala.

Material and Methods

Field Survey

Field surveys were carried out to investigate and examine the biodiversity and also to record geographical occurrence points of the study area in four districts of Kerala namely, Kasargod, Kannur, Malappuram, and Thrissur in the month of June to November (SouthWest and NorthEast monsoons) during 2023-24, where both vegetative and flowering stages were observed. A total of 10 occurrence points were documented from the above mentioned districts in Kerala (Table 1). These points were utilized as habitat representatives for *H. diphylla* and the data were subsequently subjected to further analysis.

Habitat Suitability Modelling

Ecological Niche Modelling(ENM) was used to forecast the potential distribution of species across different environments and this analysis was carried out using MaxEnt [Maxent (amnh.org), accessed on January 19, 2024]. The geographical coordinates of the study sites were recorded and used in the Modelling procedure. Bioclimatic variables, solar radiation data (January to December), and water vapour pressure data (January to December) were obtained from WorldClim (https://www.worldclim.org/). The Normalized Difference Vegetation Index (NDVI) data (January to December) was sourced from the Bhuvan portal [Indian Geo Platform of ISRO (nrsc.gov.in)].

Agroecological Zones

The agroecological zones of Kerala (2011) were obtained from the Cartography, GIS Processing, and Production unit at the Centre for Land Resource Research and Management, KAU, Thrissur. The state is divided into 13 agroecological zones of Kerala. The surveyed districts fall within the Malappuram type, Northern Midlands, Central Midlands, and Malayoram. The data was digitized and converted into ASCII format using QGIS for use in MaxEnt Modelling.

Soil Types of Kerala

Soil type information for Kerala was sourced from the Soil Survey Organization under the Department of Agriculture, Government of Kerala. The soil map was digitized and transformed into ASCII format using QGIS for incorporation into MaxEnt Modelling.

Digital Elevation Model (DEM)

The SRTM Digital Elevation Model (DEM) was obtained from the WorldClim archive and utilized to generate additional topographic variables, including slope, aspect, Terrain Ruggedness Index (TRI), and Topographic Position Index (TPI). It is a map-like depiction of the Earth's surface, where each pixel corresponds to a particular elevation (Baghdadi *et al.,* 2018).

Slope

It refers to the rate of change in altitude in the direction of steepest descent (Thomas *et al.,* 2014) and is expressed in degrees or as a percentage.

Aspect

Aspect refers to the direction in which a slope faces or the line of steepest descent (Thomas *et al.,* 2014). It is measured in degrees.

Terrain Ruggedness Index (TRI)

Topographical heterogeneity is assessed using the Terrain Ruggedness Index (TRI), which calculates the mean vertical difference between each pixel and its eight neighbouring pixels (Baghdadi *et al.,* 2018).

Topographic Position Index (TPI)

It represents the difference between the height of a specific cell and the average height of its surrounding neighbouring cells (Nair *et al.,* 2018). Positive values indicate areas that are higher than their surroundings, such as peaks and summits, while negative values denote enclosed areas like valleys and depressions. Areas that are flat or have a consistent slope are represented by values close to zero (Baghdadi *et al.,* 2018). Topographic variables such as Slope, Aspect, Topographic Position Index (TPI), and Terrain Ruggedness Index (TRI) were extracted from the Digital Elevation Model (DEM) of Kerala and converted to ASCII format using QGIS for use in MaxEnt Modelling.

Model Building and Assessment

To prepare data for MaxEnt, the geographic coordinates of 10 occurrence points were converted to CSV format using MS Excel. Environmental parameters, including bioclimatic data such as monthly temperature (°C), precipitation (mm), solar radiation (kJ/m²/day), and water vapour pressure (kPa), were downloaded from the World Climate Data Portal (https://www.worldclim.org/). The 30 arc-second resolution bioclimatic data was downloaded in GRID ('.grd') format and converted to ASCII ('.asc') using QGIS 3.28 to ensure compatibility with MaxEnt. Prediction accuracy can be affected by multicollinearity amongst variables, while selecting non-redundant variables may improve the model's performance (Saupe *et al.,* 2012). Over fitting of environmental factors was addressed by conducting correlation (r) analysis, which involved removing one variable from each pair with a correlation value (r > 0.80) (Zhan *et al.,* 2022). Thus, a correlation matrix for the environmental variables was generated using R 4.3.3. Out of the 62 original environmental variables, 40 highly correlated variables were removed. Ultimately, 22 environmental variables with correlation coefficients below 0.8 were selected as input parameters for the MaxEnt model (Table 2).

Model Tuning and Validation

The MaxEnt v3.4.4 interface was used to source the species occurrence and environmental variable data, with 75% of the data for training and 25% for testing (Thapa *et al.,* 2018). The Jackknife test was used to assess the per cent contribution and permutation importance of each variable (Zhan *et al.,* 2022). Using the "leave-one-out" method, training gain was compared by systematically removing one variable at a time (Shcheglovitova and Anderson, 2013). The MaxEnt output was an ASCII grid layer representing habitat suitability (0 = unsuitable, 1 = highly suitable) (Yang *et al.,* 2013). We classified habitat as low suitable (0-0.6), moderately suitable (0.6-0.8), and highly suitable (0.8-1.0) based on the probability of suitability, with results visualized in QGIS.

Evaluation of Model Performance

MaxEnt generates Receiver operative curve (ROC) curves, and model accuracy is measured by Area Under Curve (AUC). AUC values between 0.9 and 1 indicate high accuracy (Shen *et al.,* 2021). To predict the future distribution of *H. diphylla*, environmental data for Shared Socioeconomic Pathways (SSP) namely, SSP126, SSP245, SSP370, and SSP585 were used over four time periods (2020-2040, 2040-2060, 2060-2080, and 2080-2100). These datasets were sourced from WorldClim (MIRCO6, CMIP6) at 30-second spatial resolution.

Results

Model Evaluation and Potential Suitable Habitat for Habenaria diphylla Under Present Scenario

The Area Under Curve (AUC) values were used to evaluate the model fit in predicting the habitat suitability for the species following Zhao *et al.* (2018).

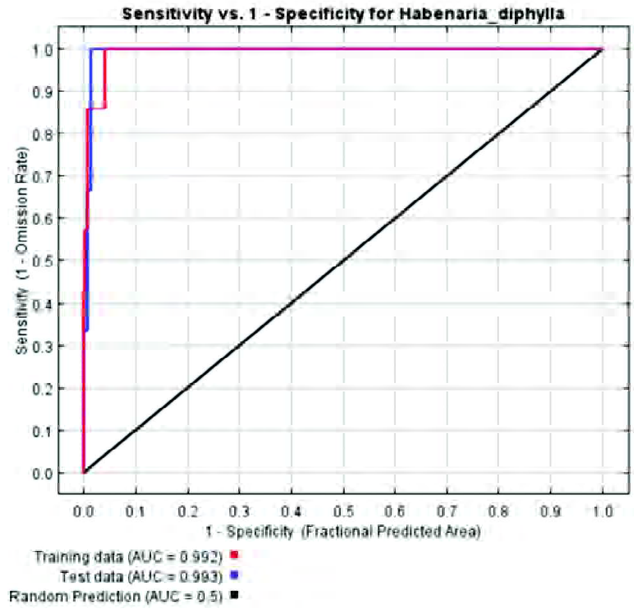

Fig. 1. Result of AUC (Area Under Curve) in developing habitat suitability model for *Habenaria diphylla*

In the present study, the AUC value was observed to be 0.992 for training data and 0.993 for the test data (Fig. 1). The areas in brown colour in the map depicts

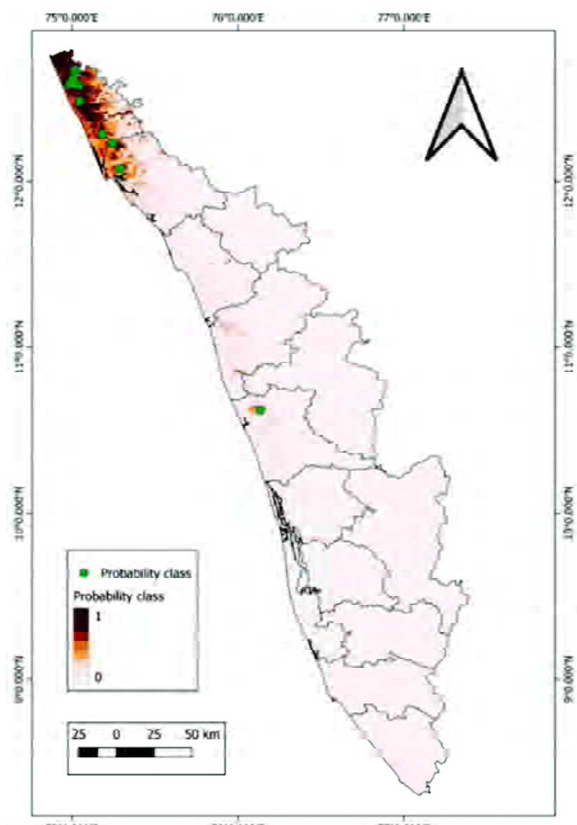

Fig. 2. Habitat suitability of *Habenaria diphylla* in the state of Kerala, India.

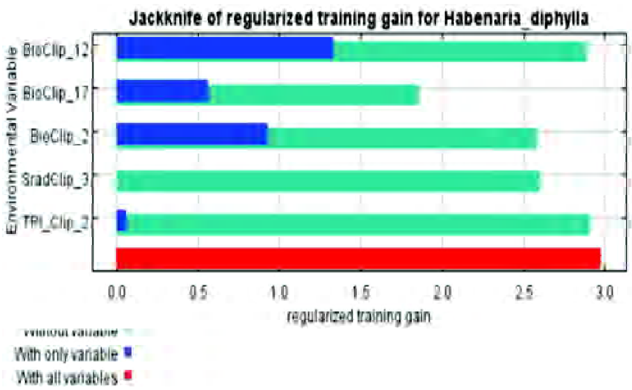

Fig. 3. Regularized training gain of dominant environmental variables using Jackknife method in *Habenaria diphylla*.

the localities that were highly suitable (0.8-1) for *H. diphylla* while those in orange colour represents medium suitable areas (0.6-0.8), and low suitable areas (0.0-0.6) were shown in light pink colour (Fig. 2). Predicted highly suitable area for *H. diphylla* by the MaxEnt model under present climatic condition was to the tune of 1344 km^2 (0.8-1.0 range) and the low suitable area was estimated to be 37519 km^2 (0-0.6 range). The habitat suitability map of *H. diphylla* indicated that high suitability areas were mainly distributed in Kasargod, Kannur, and some parts of Malappuram and Thrissur districts. It was observed that the low suitable area predominated in the Southern and Eastern parts of Kerala while the highly suitable areas were concentrated in the midlands of Central and Northern Kerala.

Relative Contribution of Dominant Environmental Variables Using Jackknife Method

The estimated contribution of the selected environmental variables to the model was analysed (Fig. 3; Table 3). The Jackknife method was used to assess the contribution of the variables in generating the habitat suitability map for *H. diphylla.* The variables namely annual precipitation (Bio12), mean diurnal range (Bio2), precipitation of driest quarter (Bio17), solar radiation (March), and Topographic Position Index (TPI) were the 5 critical predictors of the habitat model for *H. diphylla*. Their individual per cent contribution to the model was 33.2 %, 30.5 %, 24.9 %, 8.9 %, and 2.6 % respectively.

Range of Environmental Variables for the Growth of Habenaria diphylla

It was inferred from the field survey that *H. diphylla* could thrive in regions with bioclimatic variables under the present climatic scenario such as annual precipitation (Bio12) ranging from 2938 mm to 4421 mm, precipitation of driest quarter (Bio17) ranging from 7 mm to 36 mm, solar radiation (March) ranging from 23510 kJ/m^2/day to 24544 kJ/m^2/day, maximum temperature ranging from 30.5^{o}C to 31.5^{o}C and minimum temperature ranging from 21.9^{o}C to 23.5^{o}C and Topographic Position Index (TPI) ranging from 6.7 m to 80 m (Table 4).

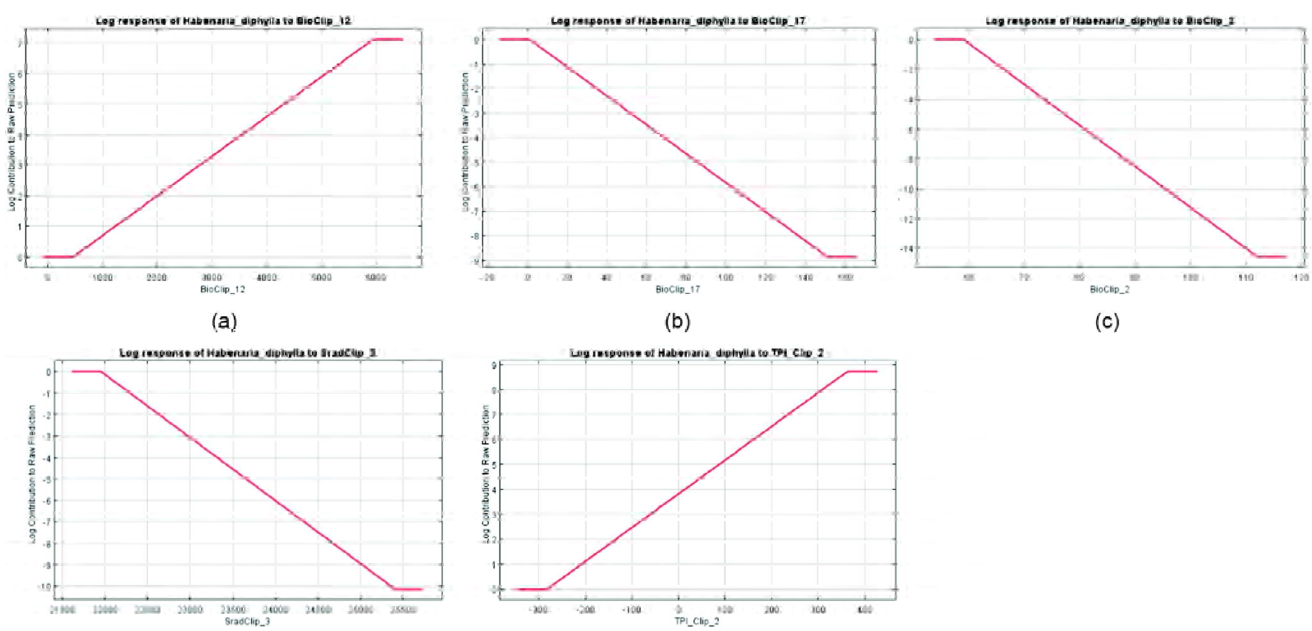

Fig. 4a-e. Marginal response curves for important environmental variables affecting the distribution of *Habenaria diphylla* in Kerala: a, Annual precipitation (Bio12); b, Precipitation of driest quarter (Bio17); c, Mean diurnal range; d, Solar radiation (March); e, Topographic Position Index (TPI).

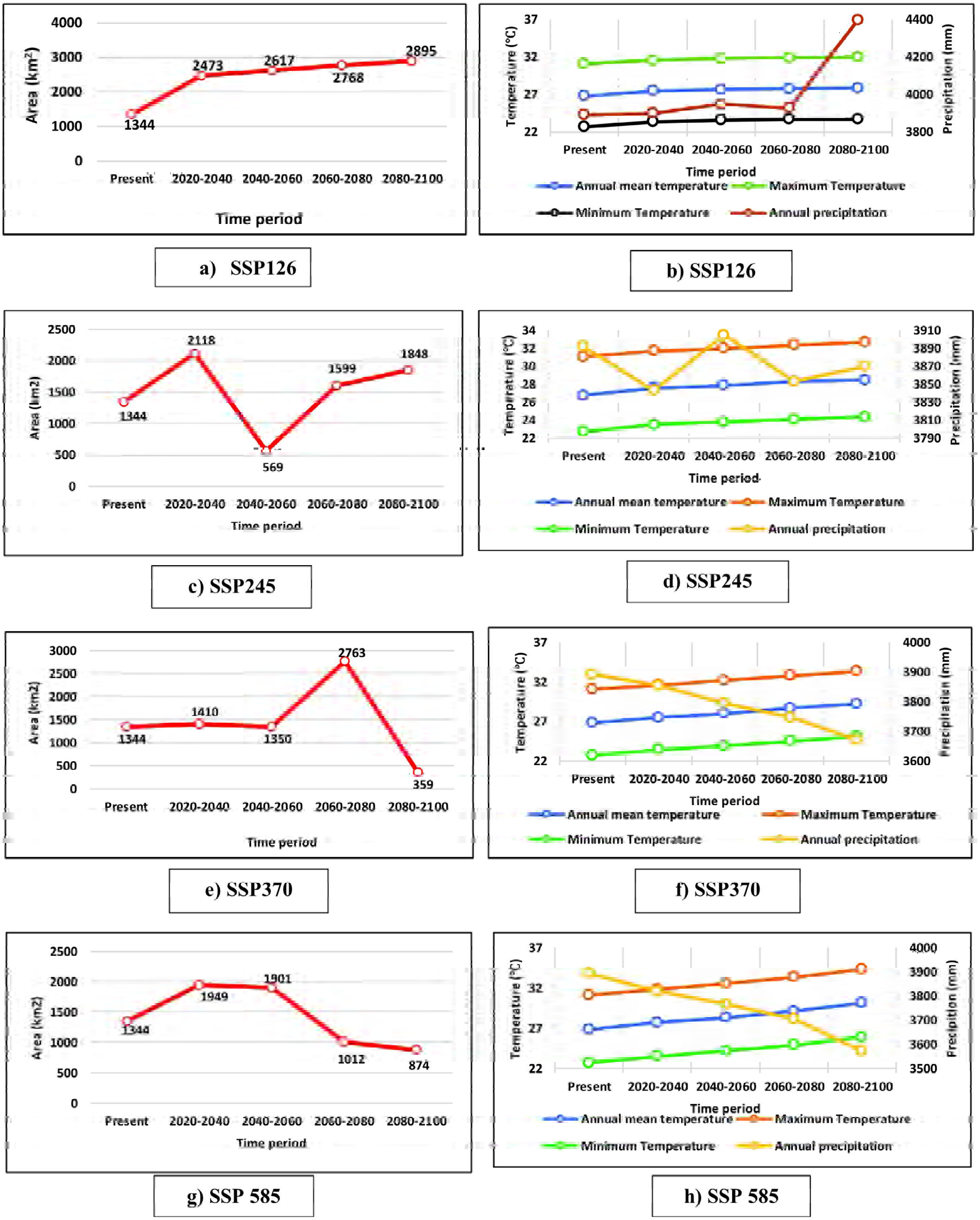

Fig. 5a-h. Area of high suitability and temperature and precipitation data at the occurrence points of *Habenaria diphylla* under SSP126, SSP245, SSP370, and SSP585 scenario.

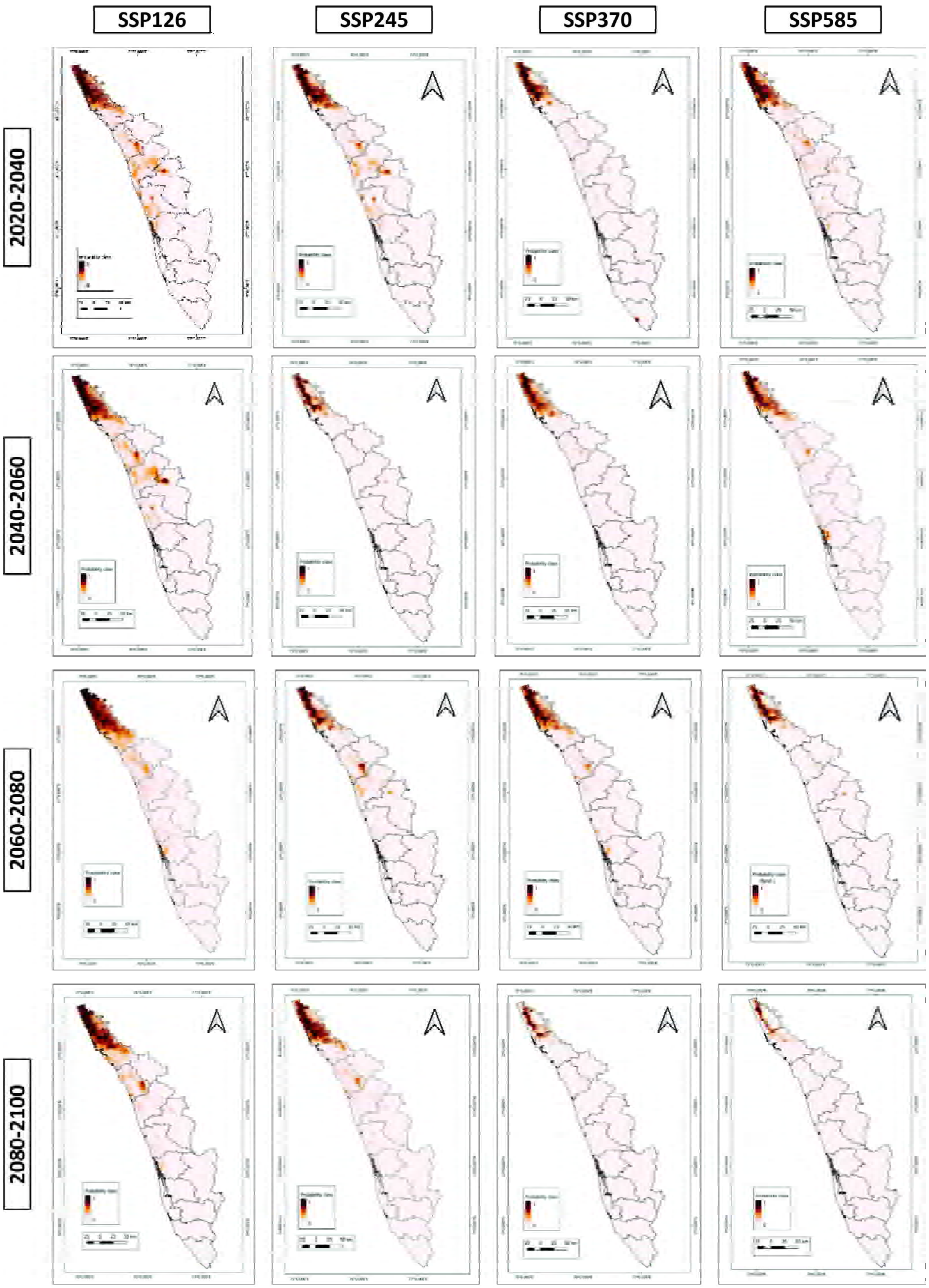

Fig. 6. Predicted future habitat suitability of *Habenaria diphylla* in Kerala under different SSP scenarios for 2021-2040, 2041-2060, 2061-2080, and 2081-2100.

Table 1. Geographical locations of *Habenaria diphylla* in various localities presently surveyed in Kasargod, Kannur, and Thrissur districts of Kerala.

Place of collection	District	Latitude(degrees)	Longitude(degrees)	Altitude (m)
Thalakottukara	Thrissur	10.6217	76.135877	34.99
Kumbla	Kasargod	12.582987	74.983635	80.99
Puthige		12.613948	75.008722	87.99
Dharmatadka		12.667981	75.024595	239.99
Kudalmarkala		12.669415	75.019698	239.99
Neerchal		12.57555	12.57555	107.9
Seethangoli		12.589287	75.010028	87.99
Thekkil		12.481575	75.04656	74.00
Cheemeni		12.230758	75.246202	88.9
Pariyaram	Kannur	12.07653	75.290232	48.99

Marginal Response Curves

A marginal response curve illustrates how the predicted suitability of habitat or species occurrence changes with incremental changes in a particular environmental variable, while keeping all other variables constant at their average values. The marginal response curve for the environmental variables which was contributing to the model revealed that the areas of habitat suitability of *H. diphylla* primarily influenced annual precipitation (Bio12): ~ 4000 to 6000 mm, mean diurnal range (Bio2): ~ 6.0^{o}C to 7.0^{o}C, precipitation of driest quarter (Bio7) 7 mm to 40 mm, solar radiation (March): ~ 22000 kJ/m^2/day, Topographic Position Index (TPI): ~ 350 m (Fig. 4).

Potential Ecologically Suitable Distribution of Habenaria diphylla Under Future Climatic Scenarios

In order to know the possible future potential distribution of *H. diphylla* in Kerala under various climatic scenarios during time periods 2020-2040, 2040-2060, 2060-2080, and 2080-2100, MaxEnt model was run using the corresponding bioclimatic variables. The four SSPs (Shared Socioeconomic Pathway) scenarios namely SSP126, SSP245, SSP370, and SSP585 were considered. The ecologically suitable distribution areas for *H. diphylla* were primarily concentrated in Kasargod, Kannur, Malappuram, Kozhikode, Palakkad, and Thrissur under all Shared Socioeconomic Pathways (SSPs) scenarios.

SSP126

The AUC values for training data were 0.992 (present scenario), 0.985 (2020-2040), 0.998 (2040-2060), 0.982 (2060-2080), and 0.978 (2080-2100). The AUC values for test data were 0.993 (present scenario), 0.996 (2020-2040), 0.971 (2040-2060), 0.994 (2060-2080), and 0.993 (2080-2100) as shown in Table 5. It indicated a good

Table 2. Environmental variables with correlation <0.8.

Environmental parameters	Unit
Bio1- Annual Mean Temperature	^{o}C
Bio2 - Mean diurnal range	^{o}C
Bio3 - Isothermality	^{o}C
Bio12- Annual precipitation	mm
Bio15 - Precipitation seasonality	mm
Bio17- Precipitation of driest quarter	mm
Bio18 - Precipitation of warmest quarter	mm
Srad_1 - Solar radiation (January)	kJ/m^2/day
Srad_3 - Solar radiation (March)	kJ/m^2/day
Srad_6 - Solar radiation (June)	kJ/m^2/day
Srad_7 - Solar radiation (July)	kJ/m^2/day
Srad_9 - Solar radiation (September)	kJ/m^2/day
Srad_10 - Solar radiation (October)	kJ/m^2/day
Water vapour pressure	kPa
Agro-ecological zones of Kerala1) Central midlands, 2) Chittor black soils, 3) Coastal sandy, 4) High ranges, 5) Kuttanad, 6) Malappuram type, 7) Malayoram, 8) Northern midlands, 9) Onattukara, 10) Palakkad plains, 11) Red loam, l2) Southern midlands, and 13) River bank alluvium.	
Soil types of Kerala1) Coastal alluvium, 2) Alluvium, 3) Acid saline, 4) Kari soil, 5) Laterite soil, 6) Red soil, 7) Hill soil, 8) Black cotton soil, and 9) Forest soil.	
Elevation (DEM)	m
TRI - Terrain Ruggedness Index	m
TPI - Topographic Position Index	m
Slope	%
Aspect	Degree
NDVI - Normalized Difference Vegetation Index (August 31st)	Ratio

Table 3. Contribution of Environmental variables in distribution Modelling of *Habenaria diphylla.*

Variables	Per cent contribution
Annual precipitation (Bio12)	33.2
Mean diurnal range (Bio2)	30.5
Precipitation of driest quarter (Bio17)	24.9
Solar radiation (March)	8.9
Topographic Position Index (TPI)	2.6

model fit for the different future scenarios.

The area of high suitability of *H. diphylla* increased from 1344 km^2 (present scenario) to 2473 km^2 (2020-2040), 2617 km^2 (2040-2060), 2768 km^2 (2060-2080), and 2895 km^2 (2080-2100) with percentage increase of 84%, 94.7%, 105%, and 115%, respectively (Fig. 5a).

The annual mean temperature extracted from the bioclimatic data set for *H. diphylla* varied from 26.8 °C (present scenario) to 27.5°C (2020-2040), 27.7°C (2040-2060), 27.8 °C (2060-2080), and 27.9°C (2080-2100). Maximum temperature extracted from the bioclimatic datasets varied from 31.1°C (present scenario) to 31.6°C (2020 -2040), 31.8°C (2040-2060), 31.9°C (2060-2080), and 32°C (2080-2100). The minimum temperature observed were 22.7 °C (present scenario) to 23.4°C (2020-2040), 23.6°C (2040-2060), and 23.7°C (2060-2080 and 2080-2100). Rainfall increased from 3892 mm (present scenario) to 3900 mm (2020-2040), 3948 mm (2040-2060), decreasing to 3929 mm (2060-2080), and again increased to 4398 mm (2080-2100). In general, there was an increase in rainfall throughout the periods and the mean temperature also showed an increasing trend (Fig. 5b).

SSP245

The AUC value for training data was 0.992 (present scenario), 0.985 (2020-2040), 0.998 (2040-2060), 0.993 (2060-2080), and 0.978 (2080-2100). The AUC value for test data was 0.993 (present scenario), 0.996 (2020-2040), 0.971 (2040-2060), 0.994 (2060-2080), and 0.993 (2080-2100) (Table 6).

The area of high suitability for *H. diphylla* was found to increase from 1344 km^2 (present scenario) to 2118 km^2 for the period 2020-2040 with percentage increase of 57.5 %, and area was decreased to 569 km^2 for the period 2040-2060 with percentage decrease of 57.6 % and area again increased to 1599 km^2 for the period 2060-2080 with a percentage increase of 18.9 % and 1848 km^2 for the period 2080-2100 with percentage increase of 37.5 % corresponding to the present scenario (Fig. 5c).

The annual mean temperature extracted from the bioclimatic data set for *H. diphylla* varied from 26.8°C (present scenario) to 27.6°C (2020-2040), 27.9°C (2040-2060), 28.3°C (2060-2080) and 28.5°C (2080-2100). Maximum temperature extracted from the bioclimatic datasets varied from 31.1°C (present scenario) to 31.7°C (2020-2040), 32°C (2040-2060), 32.4°C (2060-2080) and 32.7°C (2080-2100). The minimum temperature observed were 22.7°C (present scenario) to 23.5°C (2020-2040), 23.8°C (2040-2060), 24.1°C (2060-2080) and 24.4°C (2080-2100). Rainfall decreased from 3892 mm (present scenario) to 3843 mm (2020-2040) and increases to 3905 mm (2040-2060), and again decreases 3853 mm (2060-2080) and 3838 mm (2080-2100). In general, rainfall and temperature had shown increasing trend (Fig. 5d).

SSP370

The AUC value for training data was 0.992 (present scenario), 0.992 (2020-2040), 0.983 (2040-2060), 0.973 (2060-2080) and 0.998 (2080-2100). The AUC value for test data was 0.993 (present scenario), 0.998 (2020-2040), 0.996 (2040-2060), 0.997 (2060-2080), and 0.962 (2080-2100) (Table 7).

4. Descriptive statistics of the environmental variables at the occurrence points of *Habenaria diphylla* which were considered for the model run.

Variables	Minimum value	Maximum value	Mean ± SD
Annual Mean Temperature (°C)	26.2	27.2	26.8 ± 4.0
Maximum Temperature (°C)	30.5	31.5	31.1±2.2
Minimum Temperature (°C)	21.9	23.5	22.7±2.0
Mean diurnal range (°C)	7.0	7.6	7.2 ±1.8
Annual precipitation (mm)	2938	4421	3892 ± 488
Precipitation of driest quarter (mm)	7	36	13.41 ± 10.74
Solar radiation (March) (kJ/m^2/Day)	23510	24544	24096 ± 358
Topographic Position Index (TPI)	6.7	80	26.3 ± 25.7

The area of high suitability of *H. diphylla* increased from 1344 km^2 (present scenario) to 1410 km^2 for the time period 2020-2040, 1350 km^2 for the time period 2040-2060, 2763 km^2 for the time period 2060-2080 with percentage increase of 4.9 %, 0.4 %, and 105 % with respectively and the area was decreased to 359 km^2 for the period 2800-2100 with percentage decrease of 73.2 % (Fig. 5e).

The annual mean temperature extracted from the bioclimatic data set for *H. diphylla* varied from 26.8°C (present scenario) to 27.5°C (2020-2040), 28°C (2040-2060), 28.7°C (2060-2080), and 29.2°C (2080-2100). Maximum temperature extracted from the bioclimatic datasets varied from 31.1°C (present scenario) to 31.6°C (2020 -2040), 32.2°C (2040-2060), 32.8°C (2060-2080), and 33.3°C (2080-2100). The minimum temperature observed were 22.7°C (present scenario) to 23.4°C (2020-2040), 23.9°C (2040-2060), 24.5°C (2060 -2080), and 25.1°C (2080-2100). Rainfall decreased from 3892 mm (present scenario) to 3854 mm (2020-2040), 3795 mm (2040-2060), 3746 mm (2060-2080), and 3671 mm (2080-2100). In general, there was a decrease in rainfall, area, and temperature had shown increasing trend (Fig. 5f).

SSP585

The AUC value for training data was 0.992 (present scenario), 0.981 (2020-2040, 2060-2080 and 2080-2100), and 0.978 (2040-2060), The AUC value for test data was 0.993 (present scenario), 0.999 (2020-2040 and 2040-2060), 0.998 (2060-2080), and 0.989 (2080-2100) (Table 8).

The area of high suitability of *H. diphylla* increased from 1344 km^2 (present scenario) to 1949 km^2 for the period 2020-2040, 1901 km^2 for the period 2040-2060 with percentage increase of 45 %, 41.4 %. For the period of 2060-2080 and 2080-2100 the area of high suitability decreased with values 1012 km^2 and 874 km^2 with percentage decrease of 0.24 % and 0.35 %, respectively (Fig. 5g).

The annual mean temperature extracted from the bioclimatic data set for *H. diphylla* varied from 26.8°C (present scenario) to 27.7°C (2020-2040), 28.3°C (2040-2060), 29.1°C (2060-2080), and 30.1°C (2080-2100). Maximum temperature extracted from the bioclimatic datasets varied from 31.1°C (present scenario) to 31.8°C (2020 -2040), 32.5°C (2040-2060), 33.3°C (2060-

Table 5. AUC values of training and test data of the model for SSP126 scenario.

Area under curve (AUC)	Present scenario	2020-2040	2040-2060	2060-2080	2080-2100
Training data	0.992	0.985	0.998	0.982	0.978
Test data	0.993	0.996	0.971	0.994	0.993

Table 6. AUC values of training and test data of the model for SSP245 scenario.

Area under curve (AUC)	Present scenario	2020-2040	2040-2060	2060-2080	2080-2100
Training data	0.992	0.985	0.998	0.982	0.978
Test data	0.993	0.996	0.971	0.994	0.993

Table 7. AUC values of training and test data of the model for SSP370 scenario.

Area under curve (AUC)	Present scenario	2020-2040	2040-2060	2060-2080	2080-2100
Training data	0.992	0.992	0.983	0.973	0.998
Test data	0.993	0.998	0.996	0.997	0.962

Table 8. AUC values of training and test data of the model for SSP370 scenario.

Area under curve (AUC)	Present scenario	2020-2040	2040-2060	2060-2080	2080-2100
Training data	0.992	0.981	0.978	0.981	0.981
Test data	0.993	0.999	0.999	0.998	0.989

2080), and 34.3°C (2080-2100). The minimum temperature observed were 22.7°C (present scenario) to 23.5°C (2020-2040), 24.2°C (2040-2060), 24.9°C (2060-2080), and 25.9°C (2080-2100). Rainfall decreased from 3892 mm (present scenario) to 3818 mm (2020-2040), 3765 mm (2040-2060), 3705 mm (2060-2080), and 3571 mm (2080-2100). In general, rainfall and area had shown decreasing trend (Fig. 5h).

Discussion

Habitat Suitability Modelling

The present study employed species distribution Modelling techniques to assess potential changes in the distribution of suitable habitats for the medicinal orchid, *Habenaria diphylla*, in Western Ghats of Kerala, India. This technique may prove to be as one of the most crucial tools for identifying shortcomings in nature management strategies and evaluating species response to climate change. This species thrives well in secondary/mixed forest wetland areas under canopy, alongside *Cratoxylum formosum*, *Curculigo annamitica*, *Curcuma pierreana,* and *Eurycoma longifolia* (Van *et al.,* 2021). It typically grows in semiarid grassland (Jalal and Jayanthi, 2018). Vietnam's Decree 06/2019/ND-CP regulates the trade and exploitation of orchid species and categorizes them in Group II, to prevent over exploitation and this helps to ensure their survival (Van *et al.,* 2021). Utilizing CMIP6 data, the present study employed MaxEnt (3.4.4), QGIS (3.28), and RStudio (4.3.3) to model and map the potential distribution of *H. diphylla* in Western Ghats, Kerala, India, under current and future scenarios, highlighting cultivation planning and conservation efforts.

Influence of Environmental Variables in Species Distribution Modelling of Habenaria diphylla

AUC values less than 0.75 are considered as poor descriptors, whereas values above 0.75 indicate a good fit for the model (Wei *et al.,* 2020). The model showed high predictive accuracy, with Area Under the Curve (AUC) value of 0.992 for training data and 0.993 for test data. Additionally, the predictions of the model are closely aligned with the actual geographical distribution of *H. diphylla* in Kerala. The present results indicated that precipitation of driest quarter (Bio17), annual precipitation (Bio12), mean diurnal range (Bio2), solar radiation (March), Topographic Position Index (TPI), were the most critical variables to generate habitat suitability map of *H. diphylla*. The Topographic Position Index (TPI) varied from 6.7 to 80 meters, with optimal habitat suitability. TPI values near zero signify flat areas, while values greater than zero represent constant slope areas (Seif, 2014). In the present study, the plant was predominantly found in areas with constant slopes, characterized by TPI values greater than zero.

Impact of Climate Change in Future Scenario

Among all four SSP scenarios, SSP585 is identified as the worst-case climate change scenario, with devastating consequences (Zhang *et al.,* 2022). Under current climate, MaxEnt estimated that the highly suitable areas of *H. diphylla* were mainly distributed Kasargod, Kannur, Malappuram and Thrissur with an area of 1344 km^2. In future climatic scenarios under SSP126, the area of high suitability increased throughout the period. Under SSP245, the area of high suitability increased throughout the period except for 2040-2060, where it decreased by 57.66 % corresponding to the present scenario. Under SSP370, the area of high suitability increased throughout the period except for 2080-2100, where it decreased by 73.28 % with respect to the present scenario. SSP585 scenarios showed an increased area of high suitability throughout the time period except for 2060-2080 and 2080-2100 where the area of high suitability decreased by 0.24% and 0.35%, respectively. Climate Modelling reveals contrasting impacts on suitability habitat of *H. diphylla* in Kerala. SSP126 and SSP245 scenarios showed increasing high-suitability areas (2020-2100), whereas SSP370 and SSP585 scenarios exhibited declining suitability, particularly in Malappuram and Thrissur districts, by 2080-2100.

Conclusion

The present findings indicate significant impacts of anthropogenic activities and climate change on the distribution patterns in the studied districts of Kerala, highlighting the need for urgent conservation measures to mitigate these pressures. The present research also utilized MaxEnt Modelling to forecast habitat suitability of terrestrial orchid *Habenaria diphylla* under current and future climate conditions. Scenario analysis indicated that highly suitable area of *H. diphylla* will increase under SSP126 (RCP2.6) and SSP245 (RCP4.5), but decrease under SSP370 (RCP6.0) and SSP585 (RCP8.5) scenarios. The findings of the present study provide crucial insights for developing conservation strategies to protect *Habenaria diphylla* is a terrestrial orchid of significant medicinal and ornamental value. Orchids, with their intricate life cycles, are highly vulnerable to habitat destruction, climate change, and unsustainable harvesting, posing significant threats to their survival. To safeguard orchid diversity, research is essential in critical biological areas, including pollination mechanisms, mycorrhizal partnerships, genetic diversity, and spatial distributions.

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