

MaxEnt modeling in predicting habitat suitability for *Syzygium alternifolium* - An endangered species from Eastern Ghats, India.

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Abstract

Syzygium alternifolium (Wight) Walp. is a medium-sized tree economically exploited locally for its medicinal uses. Its seeds, fruit pulp, leaves and bark are used locally in ayurvedic medicines for the treatment of various ailments. It is an endemic and endangered species that is narrowly confined to the southern parts of Eastern Ghats, India. To understand its ecological and geographic distribution and to identify potential habitats for its introduction/reintroduction to assist its recovery from the endangered category, we used MaxEnt for ecological niche modeling (ENM), taking one hundred sixty-six species occurrences and twenty-six climatic and topographical datasets as input. The MaxEnt model has identified five variables having maximum bearing on *S. alternifolium* distribution and has successfully reconstructed the species' geographic distribution in the Seshachalam, Veligonda and Lankamalla hill ranges of Eastern Ghats. The model predicts 95% of the study area to be potentially least suitable for *S. alternifolium*, whereas only 5% of the study area is predicted to be moderate to highly potentially suitable for the species. Furthermore, the model identified novel, potential habitats with similar ecological conditions that can be used as a guide for the introduction/reintroduction of *S. alternifolium* to expand its range and assist in species recovery from its endangered category.

Introduction

Syzygium is an important genus, comprising approximately 1,200 species worldwide (Parnell et al. 2007). Its natural range is spread over the tropical regions of Africa, South & Southeast Asia, Malaysia, Australia and the Pacific islands. Despite the large diversity and species richness of the genus, only a few species are commercially exploited for timber (e.g., *S. aqueum*, *S. bracteatum*), spices (e.g., *S. aromaticum* and *S. polyanthum*) and edible fruits (e.g., *S. cumini*, *S. samarangense*, *S. malaccense*, *S. jambos*). There are approximately 102 species reported from India, of which 44 are endemic to the country (Shareef and Kumar 2020). The richest diversity and endemism are seen in Western Ghats (54 species with 28 endemics), followed by northeastern India (48 species with 8 endemics) and Andaman-Nicobar islands (22 species with 4 endemics). As per the IUCN Red List, 18 species are categorized as threatened.

Syzygium alternifolium is an endemic species found narrowly distributed in the tropical dry deciduous forests of the Seshachalam, Veligonda and Lankamalla hills of Eastern Ghats in the Indian Peninsula. The species is locally used for small timber, edible fruits and as medicine. Seeds, fruit pulp, leaves and bark are used in ayurvedic medicines for the treatment of various ailments (Reddy et al. 1989, Nagaraju and Rao 1990, Rao and Rao 2001, Bakshu 2002). The species is included in the IUCN Red List as an endangered species (A2cd) (Saha et al. 2015). Although the species is mainly distributed inside protected areas, it experiences high anthropogenic pressure in the form of unregulated harvesting for timber and medicines. Erratic flowering, bud infestation and flower predation by insects, poor fruit set, fruit predation by monkeys, bears, deer and wild boars, erratic rainfall following germination are some of the problems recorded in its natural habitat that have profound bearing on its regeneration capacity.

Ecological niche modelling (ENM) is an important tool in conservation planning of 'threatened species' that includes species categorized as Vulnerable, Endangered and Critically Endangered. The tool has the potential to predict the hitherto unknown current distribution of a species (Hipolito et al. 2015, Fois et al. 2015, Fois et al. 2018), identify climatologically similar areas for restoration and species introduction and establish *ex situ* gene conservation stands (Hu et al. 2020), understand environmental correlations with species occurrence (Monterroso et al. 2009, Searcy and Shaffer 2016), predict potential distributions for invasive species (Srivastava et al. 2021, Aidoo et al. 2022), and forecast the future distribution of species under various climate change scenarios (Coban et al. 2020, Gebrewahid et al. 2020, Zhou et al. 2021, Sreekumar and Nameer 2021). The MaxEnt software package (Phillips et al. 2006) is popular among users for ecological niche modeling. MaxEnt takes into account presence-only data of species occurrence and a set of environmental predictors across a user-defined landscape as input for building the predictive model. With this in background, the present study was undertaken with the objectives of (i) exploring environmental variables and their correlations with the occurrence of *S. alternifolium* and (ii) identifying potentially suitable habitats for *S. alternifolium* introduction/reintroduction.

Materials And Methods

Study area

The Eastern Ghats are 'tors' of geological antiquity and primarily harbour tropical deciduous vegetation. The study area is located in the southern parts of Eastern Ghats bounded by 13.59999-14.72499°N latitudes and 78.74166-79.59166°E longitudes, comprising parts of Sri Venkateswar National Park and parts of the Rajampet, Kadapa and Nellore Forest Divisions in Andhra Pradesh. Background points were selected from this area for model building and validation. A comparatively larger area bound by 13.59999-15.22499°N latitudes and 78.39166-79.68333°E longitudes, where the species is most likely to move in the absence of dispersal barriers, was chosen for model projection. The terrain of the study area is hilly with steep slopes, deep valleys and plateau land on the hill top. The principal forest types include (i) southern tropical dry deciduous forests, (ii) dry red sander-bearing forests, and (iii) southern dry mixed deciduous forests. *Pterocarpus santalinus*, *Shorea tumbuggaia*, *Terminalia pallida*, *Shorea talura*, and *Cycas beddomei* are some of the associated species in the study area.

Occurrence data

Targeted field surveys were conducted during 2018, 2019 and 2021 to acquire current distribution data on *Syzygium alternifolium* populations. Altogether, the presence of only GPS coordinates of one hundred sixty-six individuals was recorded using a hand-held Garmin GPS 72H.

Environmental and topographic data

Nineteen 'Bioclimatic Variables' derived from globally interpolated datasets of monthly temperature and precipitation (Hijmans et al. 2005) at a 30-second spatial resolution were downloaded from WorldClim version 2.0. The digital elevation model (DEM) was obtained from the global data (GTOPO30) available with the United States Geological Survey (USGS) database and used to generate slope, aspect and elevation layers. We also included four other variables, viz., biological richness, disturbance index, fragmentation and vegetation, sourced from the Indian Institute of Remote Sensing, Dehradun.

Raster preprocessing

All predictor variable layers were set to a spatial resolution of 30 arc sec (~ 1 km) and the projection of World Geodetic System 84 (WGS 1984). All layers were clipped to the extent of the study area using GIS software QGIS 3.16.9. Correlation analysis among the raster layers of 26 predictor variables was performed to identify and exclude highly correlated ($r > 0.75$) variables from the study to avoid multicollinearity (Merow et al. 2013). We selected thirteen predictor variables (Table 1) with correlations below this threshold to build the model.

Table 1

Multicollinearity test (Pearson correlation coefficient, r) among the predictor variables

	Aspect	Bio1	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19	Bio2	Bio3	Bio4	Bio5	B
Aspect	1	-0.05	-0.05	-0.05	-0.04	-0.06	-0.03	-0.07	-0.06	-0.07	0.04	-0.07	-0.06	-0.04	-0.04	-0.05	-0
Bio1		1	0.99	0.99	0.25	0.16	-0.32	0.48	0.36	-0.07	0.19	0.14	0.32	0.02	0.59	0.98	0.
Bio10			1	0.98	0.24	0.12	-0.36	0.46	0.33	-0.12	0.25	0.09	0.31	-0.03	0.66	0.98	0.
Bio11				1	0.23	0.14	-0.33	0.50	0.35	-0.07	0.16	0.13	0.36	0.09	0.50	0.97	0.
Bio12					1	0.86	0.60	0.08	0.95	0.75	0.31	0.85	-0.51	-0.56	0.30	0.16	0.
Bio13						1	0.74	0.16	0.88	0.85	-0.07	0.95	-0.54	-0.49	0.13	0.04	0.
Bio14							1	-0.33	0.51	0.92	-0.21	0.74	-0.50	-0.29	-0.23	-0.41	-0
Bio15								1	0.37	-0.15	0.03	0.04	0.29	0.13	0.19	0.50	0.
Bio16									1	0.70	0.24	0.83	-0.39	-0.46	0.29	0.27	0.
Bio17										1	-0.19	0.89	-0.47	-0.31	-0.11	-0.18	0.
Bio18											1	-0.21	-0.05	-0.35	0.45	0.25	0.
Bio19												1	-0.53	-0.42	0.06	0.00	0.
Bio2													1	0.86	-0.10	0.45	0.
Bio3														1	-0.55	0.09	-0
Bio4															1	0.62	0.
Bio5																1	0.
Bio6																	1
Bio7																	
Bio8																	
Bio9																	
BioR																	
Dist																	
Ele																	
Frag																	
Slo																	
Veg																	

Model Development and Validation

We used the MaxEnt software package (Phillips et al. 2006) in the present study for model development and validation. We explored the effect of varying the number of background points, different regularization multipliers and varying the number of predictor variables on model performance. As the study area consisted of 8540 pixels, the background points were varied between 1000 and 9000 to empirically derive the optimum number of background points for the study. The regularization multiplier (rm) was varied between 0.1 and 3.0 to empirically derive the suitable rm value. Instead of setting aside a portion of the presence-only data for training the model and another portion for testing the model, we used tenfold cross validation to efficiently use the presence data. Other values were kept as default, and the model was run with auto features. The area under the receiving operating curve (AUC), training and test omission were used to evaluate the model's performance against null expectations. The predictor variables were narrowed down to five based on permutation importance and jackknife test importance of each variable in the model building. The final output map depicting potential habitat suitability had a range of logistic output from 0 to 1, which was simplified by reclassifying the area into four classes of potential habitats, *viz.*, (i) high potential (> 0.6), (ii) good potential ($0.4-0.6$), (iii) moderate potential ($0.2-0.4$), and (iv) least potential (< 0.2).

Results And Discussion

Merow et al. (2013) identified some key decisions about input data and settings that critically influence models fitted by MaxEnt. The first key decision is the choice of background sample that can alter the features selected by MaxEnt and the consequent variability in predictions emerging from it (Elith et al. 2010, 2011). In the present study, model performance varied with the variable number of background points (Table 2). Five thousand background points yielded better performance in terms of AUC, low training and test omission.

Table 2
Table showing comparative model performance with a variable number of background points (at a regularization multiplier of 0.5).

SI No.	Number of background points	Regularization multiplier = 0.5		
		AUC	Minimum training presence training omission	Minimum training presence test omission
1	1000	0.915	0	0.15
2	2000	0.891	0	0.30
3	3000	0.906	0	0.20
4	4000	0.900	0	0.25
5	5000	0.918	0	0.15
6	6000	0.915	0	0.20
7	7000	0.911	0	0.25
8	8000	0.888	0	0.45
9	8540 (all points)	0.901	0	0.25

The second key decision in MaxEnt is model regularization. MaxEnt selects individual features that contribute most to model fit using regularization (Philips et al. 2006). It reduces model overfitting by ensuring that the empirical constraints are not fit too precisely and by penalizing the model in proportion to the magnitude of the coefficients, thereby shrinking many coefficients toward zero and removing many features from the model (Tibshirani 1996). In the present study, the regularization multiplier was varied from 0.1 to 3.0, and the model performance in terms of AUC, training omission and test omission was observed (Table 3). A regularization multiplier value of 0.1 gave a close fit model with the highest AUC (0.951) but with high test omission (0.3). The model performance (AUC) decreased with an increase in the regularization multiplier from 0.1 to 0.3. A regularization parameter of 0.5 yielded a high AUC with low training and test omission.

Table 3
Table showing the effect of the variable regularization multiplier on model performance (number of background points – 5000, number of predictor variables – 5).

SI No.	Regularization multiplier	AUC	Minimum training presence training omission	Minimum training presence test omission
1	0.1	0.951	0	0.3
2	0.5	0.935	0	0.05
3	1.0	0.934	0	0.05
4	1.5	0.934	0	0.05
5	2.0	0.928	0	0.05
6	2.5	0.926	0	0.05
7	3.0	0.924	0	0.05

The third key decision in MaxEnt is the selection of predictors and features for model building. There are two schools of thought on the selection of predictors for model building. The first school of thought is based on machine learning that suggests including all reasonable predictors in the model and letting the algorithm decide which ones are important. The alternate school of thought recommends removing highly correlated predictors using correlation analysis, clustering algorithms, principal components analysis or some other dimension reduction method to reduce high correlation among features created by MaxEnt (Merow et al. 2013). In the present study, pairwise correlation analysis (Table 1) identified 13 highly correlated variables (with $r > 0.75$) that were eliminated from model building. The contributions of the 13 predictor variables included in the model and their permutation importance are presented in Table 4. The predictor variables were further narrowed down empirically to five based on model performance, permutation importance and jackknife test importance of each variable in the model building (Table 5).

Table 4
Contribution (%) and permutation importance (%) of predictor variables in model building (regularization multiplier 0.5; background points 5000).

Code	Environmental Variable	Unit	Percent Contribution	Permutation importance
Bio1	Annual Mean Temperature	°C	11.8	62.6
Bio3	Isothermality	-	2.0	0.2
Bio4	Temperature seasonality(Standard Deviation)	°C	2.6	4.4
Bio7	Temperature Annual Range	°C	0.4	0.5
Bio12	Annual Precipitation	mm	9.6	3.1
Bio14	Precipitation of Driest Month	mm	0	0.2
Bio15	Precipitation Seasonality	cv	0.4	0
Bio18	Precipitation of Warmest Quarter	mm	2.4	3.8
Bio19	Precipitation of Coldest Quarter	mm	1.0	1.1
Ele	Elevation	m	57.4	7.9
BioR	Biological Richness		1.3	3.2
Dist	Disturbance Index		10.8	12.9
Veg	Vegetation		0.3	0.2

Table 5
Table showing comparative model performance with a variable number of predictor variables (regularization multiplier 0.5; number of background points 5000).

SI No.	Number of variables	Regularization multiplier = 0.5		
		AUC	Minimum training presence training omission	Minimum training presence test omission
1	13	0.918	0	0.15
2	7	0.931	0	0.10
3	6	0.935	0	0.05
4	5	0.935	0	0.05
5	4	0.930	0	0.05

The occurrence of *S. alternifolium* in the southern parts of Eastern Ghats can be attributed to a range of environmental factors, but five environmental factors contributed the most to the model building, viz., annual mean temperature, annual precipitation, elevation, disturbance index and temperature seasonality (Table 4). In the jackknife test (Fig. 1), the model achieved the highest gain when the variable Annual Mean Temperature was used in isolation, which therefore appears to have the most useful information by itself. The annual mean temperature at species presence locations ranged from 23.6 to 26.6°C, with a mean of 25.2°C (Table 6). Although the frequency of species occurrence was maximum in the 24–26°C range (Fig. 2), the predicted habitat suitability for *S. alternifolium* declined sharply beyond 24.0°C (Fig. 3). Likewise, the predictor variable Annual Precipitation decreased the gain the most when omitted from model building (Fig. 1), which appears to have the most information that is not present in other variables. The annual precipitation at species presence locations ranged from 619 to 829 mm, with a mean of 739.8 mm (Table 6). Although the frequency of species occurrence was highest in the 800–900 mm annual precipitation range (Fig. 4), the predicted habitat suitability declined sharply beyond 800 mm annual precipitation (Fig. 5). Furthermore, the elevation at species presence locations ranged from 452 to 926 m above msl, with a mean elevation of 668.9 m (Table 6). Although the frequency of species occurrence was highest in the 600–700 m elevation range (Fig. 6), indicating the species' preference for mid elevations, the predicted habitat suitability was high in the 450–650 m elevation range (Fig. 7). The disturbance index is yet another variable that contributed highly to the model building. The disturbance index varied from low (11–18) to high (25–28) (Table 6) at the species presence locations with maximum locations under the high disturbance regime (Fig. 8). The predicted habitat suitability declined sharply beyond the disturbance index of 28 (Fig. 9). Interestingly, the predictor variable temperature seasonality calculated based on the standard deviation of monthly temperature averages showed less deviation (Table 6) at the sample locations, indicating low temperature variability over the year. The predicted habitat suitability was high for areas with a temperature standard deviation between 3.0–3.4°C (Fig. 10).

Table 6
Summary statistics at the species occurrence points for the top five predictor variables used in model building.

Sl. No.	Predictor variable	Minimum	Maximum	Mean	Mean $\pm$ SD
1	Annual mean temperature (°C)	23.6	26.6	25.2	25.2 $\pm$ 0.949
2	Annual precipitation (mm)	619	829	739.8	739.8 $\pm$ 75.167
3	Elevation (m)	452	926	668.9	668.9 $\pm$ 138.8
4	Disturbance index	12	28	22.5	22.5 $\pm$ 5.3
5	Temperature seasonality (Standard deviation) (°C)	2.9	3.2	3.0	3.2 $\pm$ 0.079

The potential habitat suitability map generated by the MaxEnt model for *Syzygium alternifolium* (Fig. 11) overlapped the forested Seshachalam, Veligonda and Lankamalla hill ranges of Eastern Ghats. The model predicted 95% of the study area to be potentially least suitable for *S. alternifolium*, and approximately 5% of the study area (approximately 21.0 square km) is predicted to be moderate to highly potentially suitable for the species. The habitats identified in Seshachalam hills are potentially more suitable than those in the Veligonda and Lankamalla hill ranges. In Seshachalam hills, the species distribution is observed in Balapally and Chamala forest ranges that further extend north-westwards into Kodur, Rajampet, Sanipaya and Rayachoti forest ranges. Areas under the Balapally and Chamala forest ranges of the Tirupati forest division are potentially highly suitable for *S. alternifolium* and presumably hold the core population of the species. In contrast, the potential habitats identified in the Veligonda hills, comprising the Chitvel, Venkatagiri, Rapur, Badvel and Atmakur forest ranges, form a narrow strip along the hill tops of these ranges. Furthermore, the potentially suitable habitats identified in Lankamalla hills include parts of the Sidhout, Badvel and Proddutur forest ranges. The MaxEnt model identified two novel habitats, viz., the first patch comprising parts of Rayachoti and Vempally forest ranges and the second patch comprising parts of Porumamilla, Rudravaram and Giddalur forest ranges, where the occurrence of species has not been reported and habitat conditions are predicted to be potentially suitable for *S. alternifolium*.

Conclusions

The increasing number of species in the red list of threatened species is a growing concern. Developmental projects, increased dependence on forests for sustenance and livelihood, invasive species and climate change have rendered many species threatened. In light of the increased and continued threats, species recovery is the only viable option for restoring many species from extinction. It is unlikely that the endangered *S. alternifolium* extant populations will recover on their own considering the earlier described problems in its natural regeneration. Assisted natural regeneration and species introduction to suitable habitats are suggested for population recovery in the species. The MaxEnt model predicts 95% of the study area to be potentially least suitable for *S. alternifolium*. Approximately 5% of the study area (approximately 21.0 square km) is predicted to be moderate to highly potentially suitable for the species. This is the fundamental niche predicted for the species; however, the realized niche, which is affected by the biotic interactions of the species, is expected to be comparatively less, lending support to its endangered categorization in the IUCN Red List of Threatened species. The MaxEnt model has identified a couple of novel habitats in the periphery of the extant range where the species presence is not reported but the habitat conditions are potentially suitable for the species. Such areas need to be targeted for introduction of the species to expand its range and in the process assisting the recovery of the species from the endangered list.

Declarations

Acknowledgements

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Conflict of Interest

The authors declare there are no conflicts of interest.

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Figures

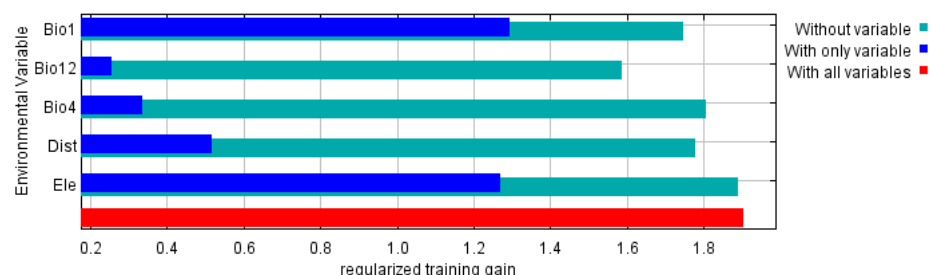


Figure 1

The jackknife test for evaluating the relative importance of environmental variables for *S. alternifolium* (Note: Bio1-Annual Mean Temperature, Bio12-Annual Precipitation, Bio4 -Temperature Seasonality, Dist-Disturbance Index, Ele-Elevation).

S. alternifolium occurrence across mean annual temperature range

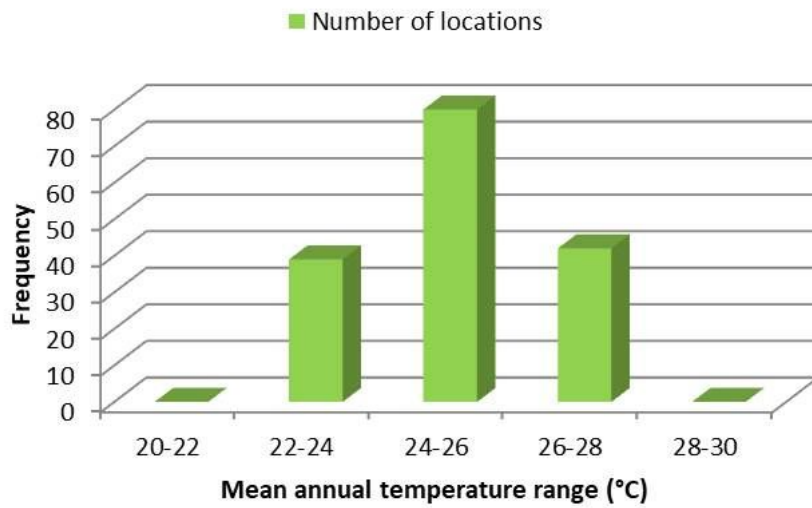


Figure 2

Frequency distribution of sample points (where occurrence of *S. alternifolium* is recorded) across mean annual temperature range.

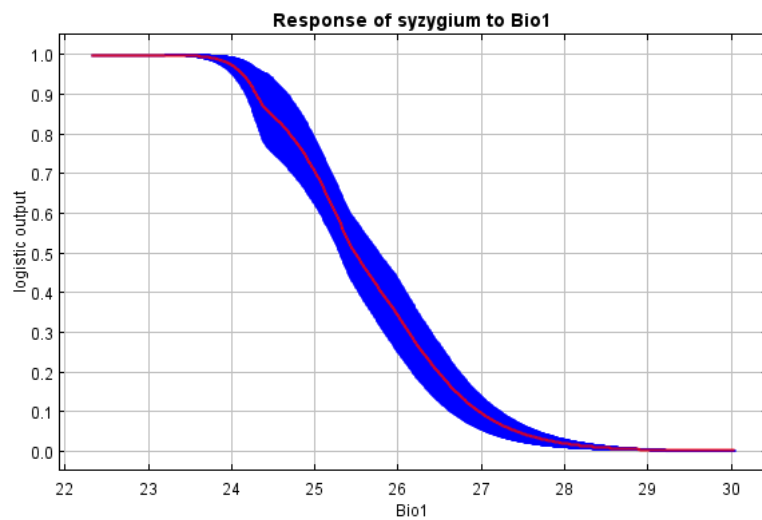


Figure 3

Marginal response curve showing response of *S. alternifolium* to Annual Mean Temperature (Bio1) (while all other environmental variables held at their average sample values).

S. alternifolium occurrence across annual precipitation range

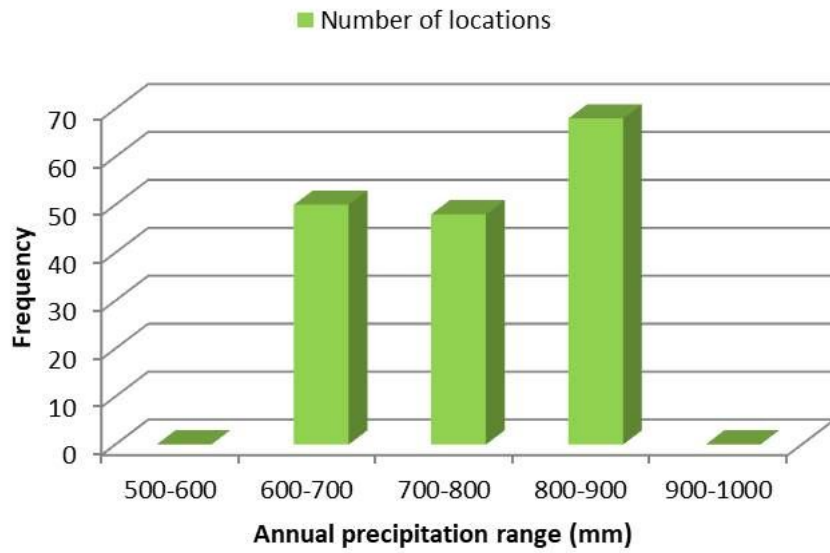


Figure 4

Frequency distribution of sample points (where occurrence of *S. alternifolium* is recorded) across annual precipitation range.

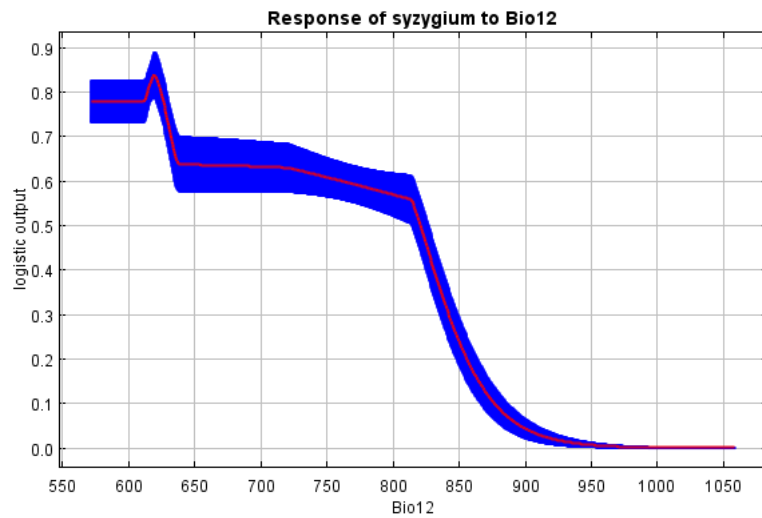


Figure 5

Marginal response curve showing response of *S. alternifolium* to Annual Precipitation (Bio12) (while all other environmental variables held at their average sample values).

S.alternifolium occurrence across elevation range

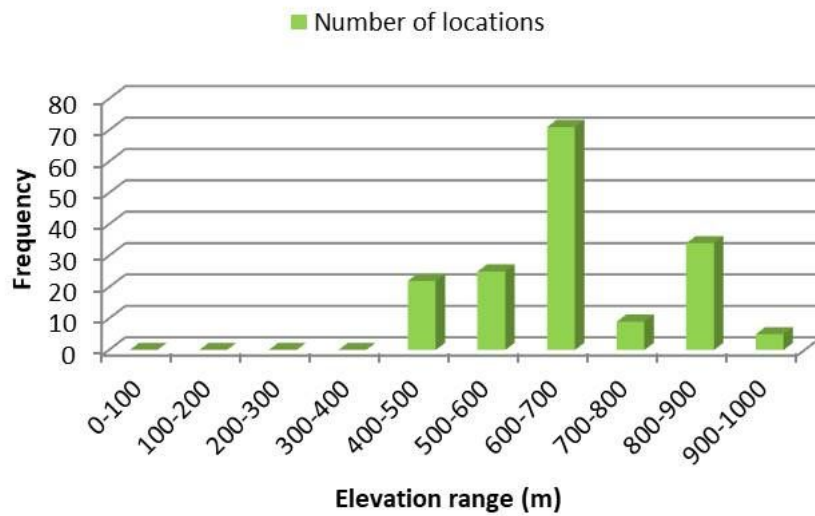


Figure 6

Frequency distribution of sample points across elevation range.

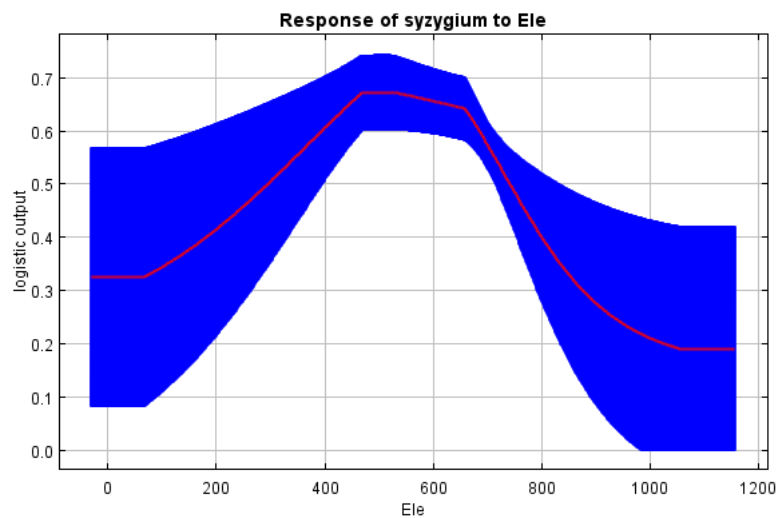


Figure 7

Marginal response curve showing response of *S. alternifolium* to elevation (while all other environmental variables held at their average sample values).

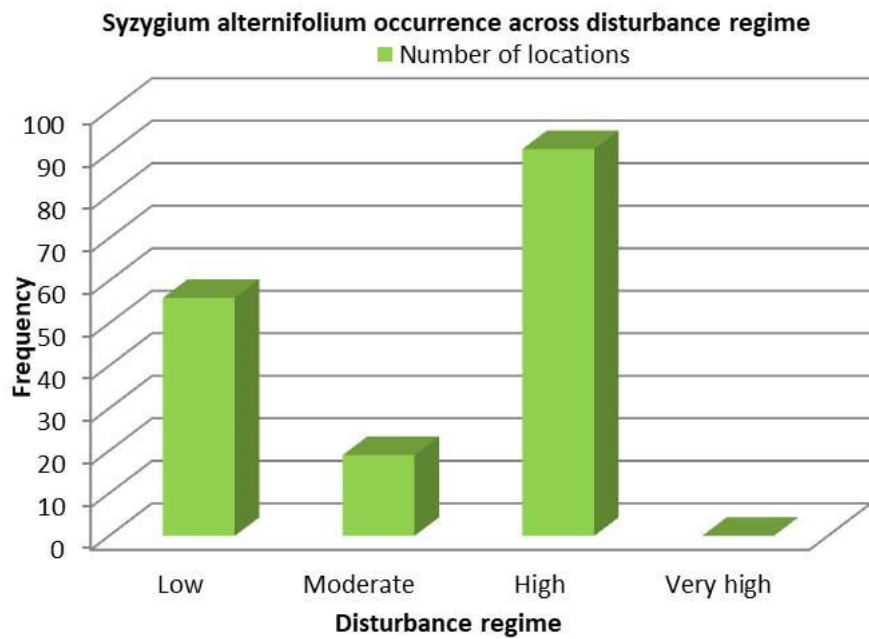


Figure 8

Frequency distribution of sample points across disturbance regime.

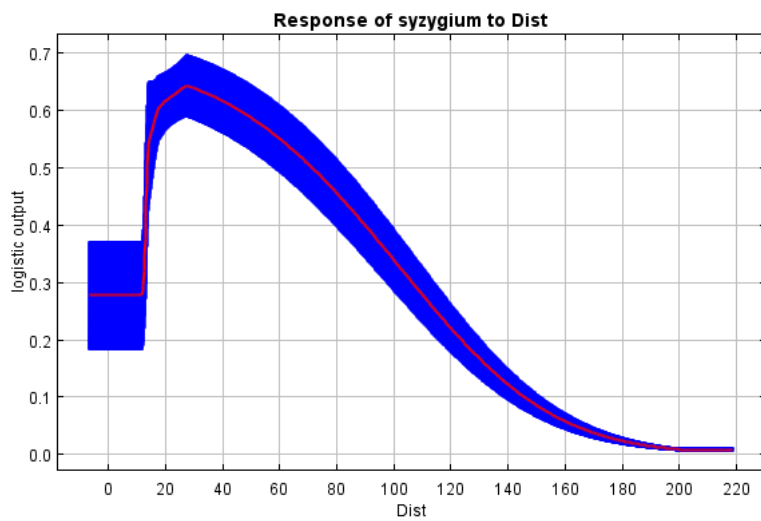


Figure 9

Marginal response curve showing response of *S. alternifolium* to disturbance regime (while all other environmental variables held at their average sample values).

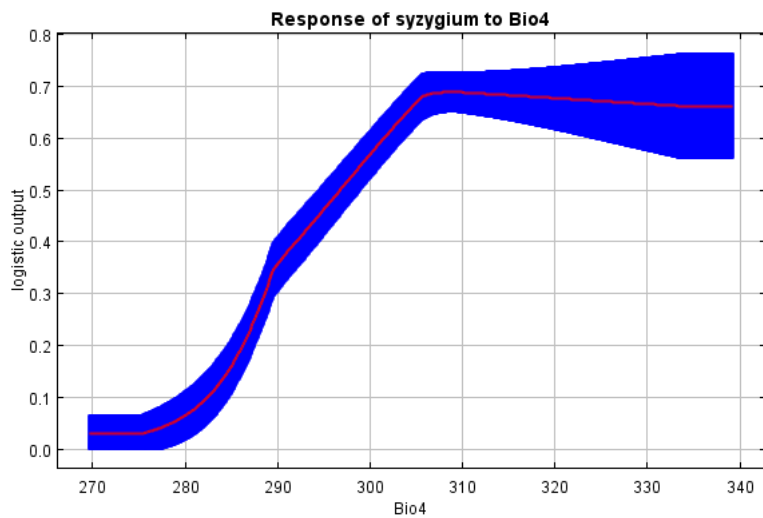


Figure 10

Marginal response curve showing response of *S. alternifolium* to temperature seasonality (standard deviation x 100) (while all other environmental variables held at their average sample values).

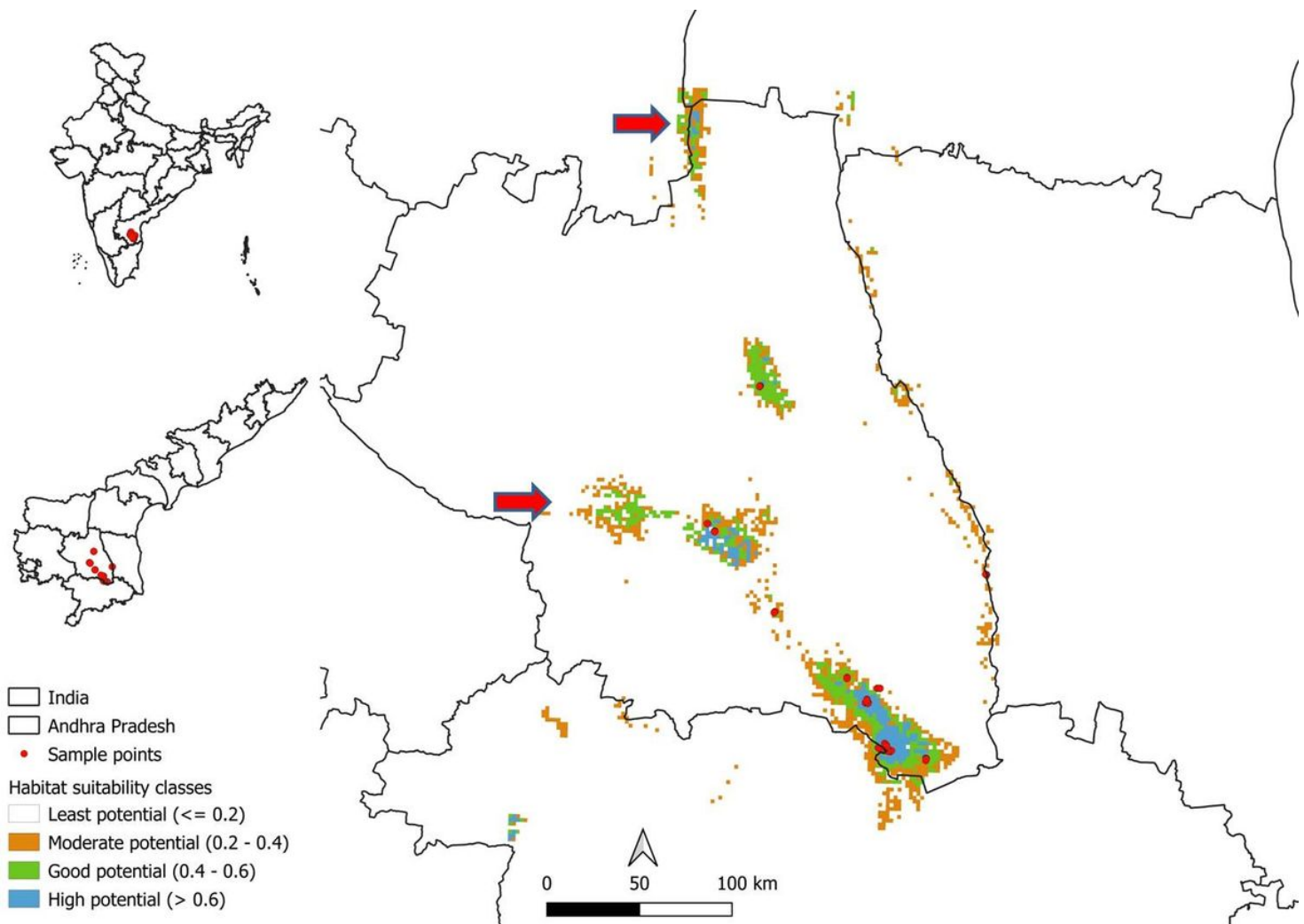


Figure 11

Predicted potential habitat suitability for *S. alternifolium* in southern parts of the Eastern Ghats, Andhra Pradesh. Red arrows indicate novel potentially suitable habitats for *S. alternifolium*.