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Species Distribution Modelling of Orchids in Telangana: Integrating ENM and Conservation Strategies

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ABSTRACT

There are few plant families as varied and vulnerable as orchids, which are renowned for their ecological sensitivity and distinctiveness. The orchid flora of Telangana, a state with diverse natural landscapes, is threatened by habitat loss, climate change, and human activity, but has received little attention from researchers. In order to forecast the present and future distribution of the rare orchid species Malaxis insignis in Telangana, this research utilizes Ecological Niche Modelling (ENM) in conjunction with environmental and bioclimatic data. The eco-physiological preferences of the species were defined using twenty bioclimatic variables taken from the WorldClim database that are physiologically significant. The model was built using MaxEnt software, which is well-known for its resilience in presence-only data modeling. Training and validation were done using 75% and 25% of the occurrence data, respectively. In order to calibrate the model, we used standard parameters and used 10,000 background points. Accuracy levels over 0.75 were indicative of good model performance when ROC-AUC and omission rates were used for evaluation. Two SRES scenarios were used to conduct future forecasts for four time periods (2020–2080) utilizing downscaled data from HadCM3 and CSIRO GCMs. To ensure the accuracy of the model, field validation was conducted in three high-probability zones where M. insignis was found. Important insights for long-term planning of orchid conservation in the face of shifting climatic scenarios are provided by this integrated method, which also identifies priority conservation zones. The research shows that environmentally vulnerable areas, such as Telangana, may benefit greatly from using ENM to direct biodiversity management and policymaking.

Keywords: Orchids, Species Distribution Modelling, Ecological Niche Modelling, MaxEnt, Conservation Strategies.

INTRODUCTION

Worldwide, there are more than 25,000 species of orchids, making them one of the most ecologically important and varied families of flowering plants. Orchids make up around 9 percent of India's plant life, and there are several rare and indigenous species among them. The Indian state of Telangana is located on the Deccan Plateau in peninsular India. Its varied terrain, climate zones, and mosaic of forest types all contribute to the possibility of microhabitats that are ideal for orchid development. Although these circumstances are ideal for orchid research, very little is known about Telangana's orchid flora. Worse worse, many native orchid species are in danger from things like habitat loss, overexploitation, and even global warming. The already precarious situation for these species is made worse by the lack of an all-encompassing ecological evaluation and conservation strategy. Ecological niche modeling, a subset of species distribution modeling (SDM), has recently come into its own as a formidable method for projecting where species may be found in the future using data on past occurrences and environmental factors. By making spatial projections of a species' ecological niche, ENM aids in comprehending species-environment connections. To map appropriate habitats and direct conservation efforts, ENM provides a dependable and cost-effective alternative to limited systematic orchid surveys in places such as Telangana. Particularly in the context of climate change scenarios, distribution patterns, both present and future, may be better understood by combining occurrence data with topography and climatic predictors.

Orchids in Telangana are known to occupy a variety of habitats, such as riparian zones, rocky hill slopes, and wet deciduous woods. The destruction and fragmentation of these ecosystems have been caused by human pressures such as urban growth, deforestation, and changing farming methods. Additionally, several populations have declined due to the illegal collecting of wild orchids for decorative and therapeutic uses. In light of this, it is of the utmost importance to determine where in the state orchids are most abundant and to determine how they spread throughout the landscape. The current research intends to use ENM methods to simulate, using occurrence data and bioclimatic factors, the distribution of several orchid species in Telangana. To create distribution maps that may be used for prediction, we utilize MaxEnt, which stands for Maximum Entropy Modeling. This is a popular presence-only modeling method. In addition to showing where appropriate habitats are located at the present time, these maps also show where there are unprotected areas of high conservation significance. Furthermore, by modeling future scenarios using climate prediction information, the research hopes to examine the possible effects of climate change on the distribution of orchids.

Closing the gap between theoretical ecological modeling and real-world conservation efforts is central to this study. The project aims to assist conservation planning and policy-making in Telangana by merging SDM data with existing protected area networks and land-use maps. Some of the conservation measures that have been suggested include the identification of biological corridors, possible areas for reintroduction, and micro-reserves for uncommon species. The study also highlights the significance of traditional knowledge, community involvement, and sustainable trading methods for orchids in protecting them for the future. The research also adds to the larger conversation about protecting biodiversity as it relates to landscape ecology and urban development. It is critical to strike a balance between development demands and ecological sustainability in Telangana, which is experiencing fast socio-economic upheaval. Because of their sensitivity to changes in their environment, orchids are often considered bioindicators. They may also be used as focus species for ecosystem monitoring. Therefore, charting their dispersion is an important step towards integrated ecological management and not just a botanical activity.

India is working hard to fulfill its obligations under international biodiversity accords like the CBD and the GSPC, making this study all the more relevant. Protecting and documenting orchid variety is in line with national goals of restoring ecosystems, making communities more resilient to climate change, and creating jobs via sustainable practices. In addition, other semi-arid and plateau areas of India may learn from Telangana's model for orchid conservation because of the state's unique biogeographical context. A scientific and strategic approach to orchid conservation in Telangana may be achieved via the integration of ENM technologies with conservation frameworks. Foundational for evidence-based biodiversity management, the research identifies distribution patterns, prioritizes conservation zones, and engages stakeholders. Protecting the region's orchids—which are rich in diversity but in danger of extinction—will need ongoing study, backing from policymakers, and education on the issue among the general public.

REVIEW OF LITERATURE

Wang, Xue-Man et al., (2023) In order to understand the basic global distribution patterns and to establish conservation priorities, orchid biogeography research using species distribution models (SDMs) is essential. The accuracy of the model relies on the consistency of the relationships between species occurrence and environmental data. Unfortunately, in modeling orchids, it's easy to forget about their specific ecological needs, such their life forms. Because of this omission, bias and increased model uncertainty may result. Even though human activities are a strong candidate for a predictor, no orchid SDMs have attempted to quantify them. We preprocessed all occurrences of orchid species based on physiological features, using the Hengduan Mountains as an example. In order to measure the interference and include it into models as an HI element, five spatial parameters linked to human activities were chosen. The research has built numerous modeling techniques using several assessment indices (AUC, TSS, and Kappa) and modeling approaches (RF, MaxEnt, and GLM). The essential zones for orchid dispersion have been chosen using a double-ranking approach. While including the HI component had a similar impact, the findings did not indicate a statistically significant improvement in accuracy compared to classification models based on physiological features. According to suitability maps, the distribution of orchids in the Hengduan Mountains relied heavily on very diverse hilly regions. Geographical differences in vegetation and climate have a larger role in the northern distribution of mycoherterophical orchids than in the southern distribution of terrestrial orchids, which predominate in mountainous locations. Because they were more temperature and precipitation sensitive, epiphytic orchids were most abundant in the southern hemisphere. Research like this helps fill gaps in our knowledge of orchid distribution in the Hengduan Mountains, which in turn encourages conservation efforts and paves the way for future studies on related topics.

Lissovsky, Andrey et al., (2021) Research on the dispersion of species throughout a given area relied only on empirical data for quite some time. The field of ecological modeling of species distribution emerged from a shift in perspective regarding species distributions as projections of Hutchinsonian ecological niches. This shift transformed faunistics and floristics from a data-gathering exercise into a fully-fledged scientific enterprise that includes experiment planning and result verification. Even when dealing with methodological obstacles such as non-randomness of occurrence data, inhomogeneity of data collection efforts, heterogeneity of landscapes at different scales, etc., the different species-distribution modeling methods allow one to examine patterns of the geographical distributional of organisms. Studies of habitats and other fields concerned with species distributions might benefit from the spatially continuous data on habitat appropriateness represented by species-distribution modeling findings.

Flores, Mayra et al., (2020) both the species' biotic interactions and their climatic connections determine the ranges of different species. Due to their exclusive focus on climate, Ecological Niche Models (ENMs) have a tendency to exaggerate the ranges of some species, particularly those that are severely constrained by biotic interactions. In order to compile this data for an ENM, we determined which host tree species Laelia speciosa prefers. We also made an effort to forecast how changes in temperature and the loss of habitat will affect the distribution of these species. L. speciosa was found as an epiphyte on six different kinds of trees, however it was only found on Quercus deserticola (96% of the individuals), suggesting a strong biotic connection. One biotic variable we included in the L. speciosa ENM is the spread of this host tree. Even though only 0.6% of L. speciosa's current distribution is located in protected areas, its total current distribution covers 52,892 km², or 4% of Mexico's landmass. For L. speciosa, the annual rate of habitat loss during the research period was 0.6%. Both the optimistic and pessimistic climate change scenarios for the years 2050 and 2070 predicted a dramatic decrease in its spread. Also, places with favorable climates will move up (by 200 to 400 meters). Improving the effectiveness of the ENMs when predicting a species' distribution by considering its interactions leads to more accurate estimations of the species' real distribution and better conservation measures.

Moreno, Juan et al., (2020) a number of species in the Orchidaceae family have had their conservation status updated using species distribution models (SDM) in recent years, which is concerning since this family is among the most endangered vascular plant groups on Earth. Having a proper understanding of how and when to apply SDM is crucial for ensuring accurate results; otherwise, conservation planners run the danger of using inaccurate models and making poor judgments. Our distribution model for Lepanthesmucronata in South America is based on the most recent and widely acknowledged information in this field. Using IUCN criteria, we assess the degree to which Colombia's protected areas are reflective of the country, the habitats in which it occurs, and the likelihood of its extinction. Based on our evaluation of these factors, the IUCN classification for Lepanthesmucronata is Least Concern (LC). For the sake of future efforts to preserve this family of plants, we hope that our inquiry will stand as a good example of this kind of examination.

Tsiftsis, Spyros & Djordjević, Vladan. (2020).Species distribution models rely heavily on biotic interactions, however they risk overestimating the probable ranges of species due to a lack of knowledge in this area. The distribution forecasts of species in the Orchidaceae family are likely to be significantly impacted by their interactions with pollinators, since these species rely heavily on mycorrhizal symbionts and other forms of pollination. This is especially true for sexually deceptive orchids, which are often extremely specialized. Using the Maxent method, we investigated the possible range of Anthophoraplagiata, a unique pollinator for two sexually deceptive orchids native to Greece (Ophrysargolica and Ophrysdelphinensis), as well as the degree to which their present and prospective habitats are suitable for these species. The distributions of the future were predicted using twelve different climate change scenarios. Precipitation seasonality for O. argolica and geological substrate for O. delphinensis were shown to be the most relevant variables influencing potential distribution, according to the results. Without considering their relationship with A. plagiata, the two orchids' present-day possible distributions were almost identical but geographically distinct. They saw a reduction in their theoretically acceptable region for both species after included the interaction in the models. The impact of the orchid-pollinator dynamic would be greater in the future climate. The distribution of O. argolica was limited to several parts of southern Greece, and the extinction of O. delphinensis was anticipated. The importance of plant-pollinator interactions in species distribution models was emphasized by our results. Serious conservation concerns can arise if these connections are not studied.

Wang, Hsiao-Hsuanet al., (2015) As a result of climate change and habitat fragmentation, endangered and vulnerable plant species are at increased risk of experiencing unstable and isolated populations, which raises serious concerns about their long-term sustainability. The greatest and most varied family of flowering plants, the Orchidaceae, is in grave danger of extinction at the present time. There has been a lot of focus on protecting rare orchids, but unfortunately, their numbers are still going down.

The central Texas-endemic Spiranthesparksii, often known as the Navasota ladies' tresses, is an endangered terrestrial orchid that is both federally and state-listed. Therefore, our goals were to establish appropriate habitat for future surveys and focused conservation initiatives, identify probable variables impacting the species' distribution, and quantify the proportional significance of each element. In order to determine probable factors that affect the chance of S. parksii occurrence, we used boosted regression trees to analyze several geo-referenced variables that describe weather and terrain aspects.

We found that climatic conditions and landscape characteristics were connected with the chance of existence, and our model accurately identified 97% of the cells in terms of species presence or absence. The most important factors were the average yearly precipitation, average height, average lowest temperature, and average maximum temperature. If S. parksii had a preferred habitat, it would be in the eastern parts of Madison and Leon counties, the southern part of Brazos, part of northern Grimes, and the border areas of Burleson and Washington counties.

By doing three things, our model can help with integrated conservation strategy development: (1) drawing attention to areas with a high probability of occurrence for future surveys and research; (2) assisting with the selection of areas for restoration and conservation; and (3) framing questions for future research, including ones that are needed to predict responses to climate change. Our approach has the potential to enhance forecast accuracy by including additional information about S. parksii as it becomes available. Additionally, our technique might be used to create distribution maps for other endangered species that are important for conservation efforts.

MATERIALS AND METHODS

Ecological Niche Modelling

Environmental Data

The distribution of species' habitats might be predicted by measuring a total of twenty bioclimatic factors. When used to characterize a species' eco-physiology, these characteristics have biological significance. Among the bioclimatic variables used in ecological niche modeling are annual patterns, seasonality, and severe or limiting environmental conditions.

It is common practice to choose bioclimatic parameters in accordance with the species' ecology. Monthly data collected from worldwide weather stations was used to establish the present climatic baseline for India in the WorldClim (WC) database. The WorldClim dataset was used to download the different bioclimatic variables. For the period between 1950 and 2000, World Clim provides interpolated global climatic surfaces based on longitude and latitude as independent variables and monthly averages of maximum and lowest temperatures and total rainfall as 2.5 arc-min grids.

Model Construction and Estimations

MaxEnt was used for modeling because it outperformed other species distribution models. For model calibration, we utilized 75% of M. insignis records as training data and 25% as test data. After 260 maximum iterations, the algorithm converged with regularization multiplier 1, 10,000 randomly selected background points as pseudo absence across the examined area.Using a continuous habitat appropriateness range from 0 (very inappropriate) to 1 (very suitable), the presence probability was described using logistic output format. Using the advanced platform Arc GIS Ver 10.0, we were able to export and view the results in the appropriate format. Future climate models will make use of the top-performing model.

The delta technique was used to downscale weather data to 30 arc seconds (1000m) to anticipate M. insignis' ideal habitat in future climates, CGIAR Research Program CCAFS data. Using two SRES emission scenarios, two GCMs—HadCM, version 3 HadCM3, and CSIRO—projected future climate for four 20-year periods (2020, 2040, 2060, and 2080). Jackknife was employed to identify informative variables.

We tested the species distribution model's accuracy and effectiveness using threshold-dependent binomial test of omission and threshold-independent ROC analysis 28,29. AUC, the area under the ROC curve, varies from zero to one.Acceptable models are those with an AUC higher than 0.75. While there could be small differences, in an ideal model the omission rate is less than 0.05. The maps were visualized using Arc GIS 10.0.

Validation of the models

We have tested and documented the models by comprehensive field surveys. So far, we have studied three places that were predicted by ENM and exhibit the greatest chance of presence of M. insignis, based on their accessibility and comparable niche habitat. Each of the four regions had a different degree of species likelihood, therefore the search radii varied from half a kilometer to one kilometer. Using GPS, the surveys were carried out.

RESULT AND DISCUSSION

Distribution and Prediction of M. insignis

Based on the known presence of M. insignis in India, the prospective distribution information was predicted using the MaxEnt niche modeling approach. Figure 1 shows the Maxent model for M. insignis, which uses Arc GIS to generate a point map showing the species' range based on verified and onsite data. Based on the present climate factors, Figure 2 shows the M. insignis forecast map. The regions with the highest probability values (0.5-1.0) are shown by the warmer colors.

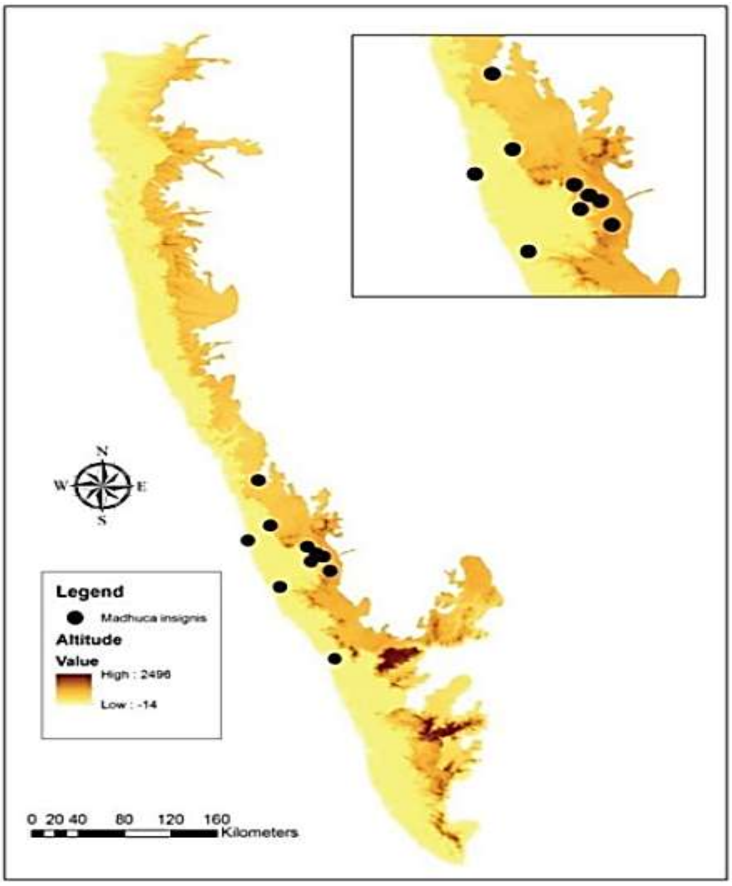

Figure 1: Geographic Range of M. insignis Mapped via ArcGIS

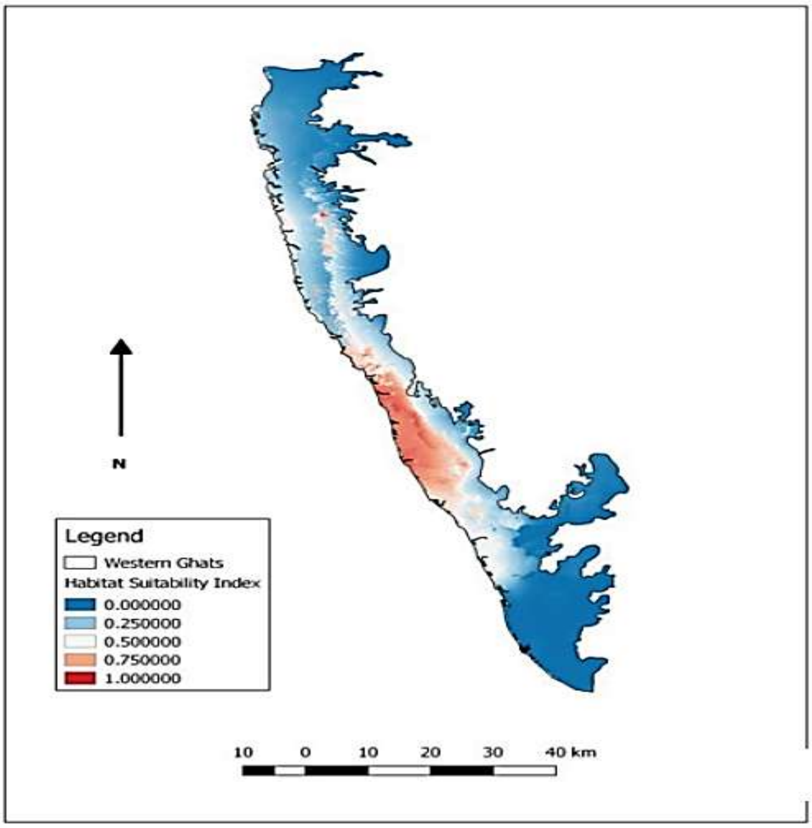

Figure 2: Potential Distribution of M. insignis Based on Spatial Modeling

Popular program that relies on maximal entropy is MaxEnt. Through the identification of nonlinear correlations between environmental factors and known locations, several studies have attempted to forecast species' ecological niches and probability distributions. In addition, MaxEnt has been used to study the effects of human activities on land use, cultural ecosystem service, and the forecast of land use events like forest fires. For purposes such as tracking disease vectors and invasive species, and to predict how they would expand due to climate change, this modeling approach has been used to predict possible insect and plant ranges. Its efficacy even on little samples is evidence that MaxEnt's multiplicative approaches outperform other techniques' discriminative methods in terms of prediction accuracy. This is a must-have since the sample size of M. insignis is so little that it often produces misleading findings like over- or under-predictions. Both the training and test sets of presence records were utilized to compute the emission rate. Cumulative threshold values should be closer to the omission rate and anticipated omission values. Using the same data supplied by MaxEnt software, Figure 3 displays the receiver ROC curve.

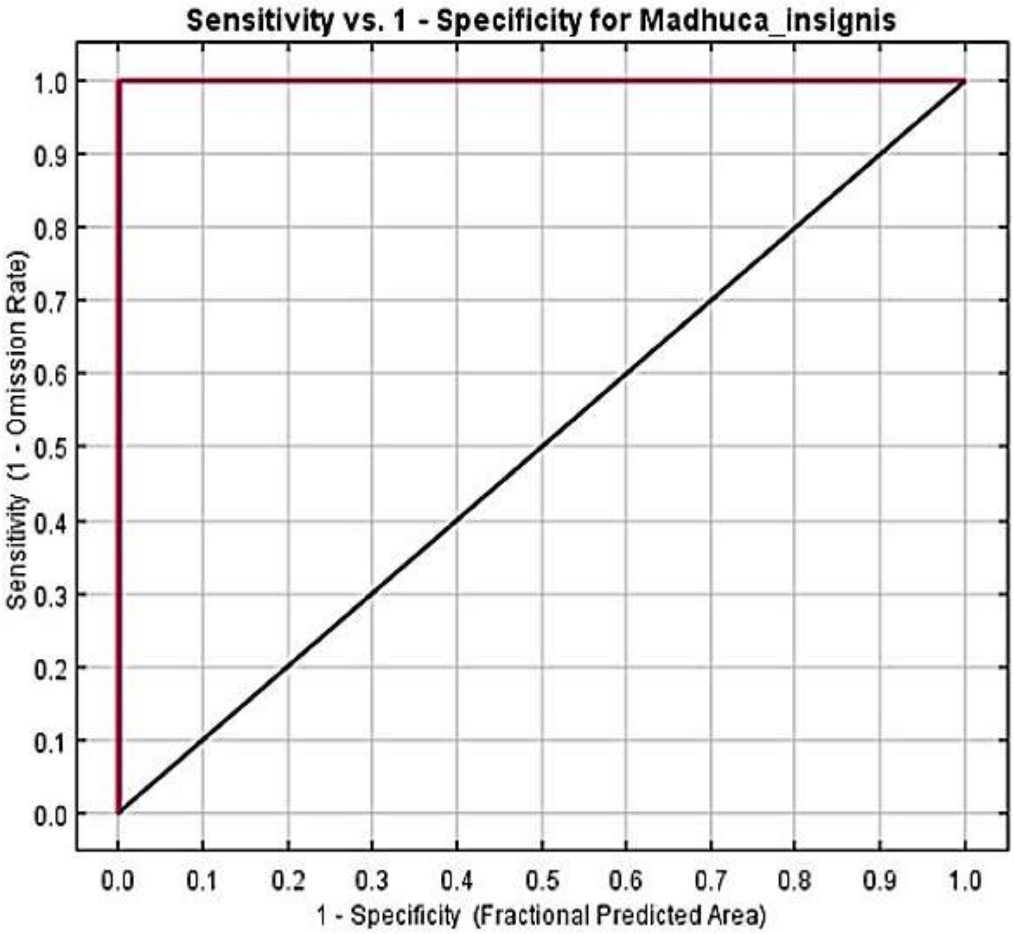

Figure 3: ROC Analysis for Validating Spatial Prediction of M. insignis

Specificity is based on predicted area, not commission. Thus, the greatest AUC is clear to be smaller than 1. If test data were from the MaxEnt distribution, the greatest possible test AUC would be 0.985 instead of 1, however it may exceed this limit. The distribution model's regularized training gain is 6.525 and training area under the curve is 1.000. However, unregularized training gain is 7.294 and test gain is 6.082. The model's prediction accuracy is typical when AUC is less than 0.7. AUC between 0.7 and 0.9 is high. When AUC exceeds 0.9, it is unusual.

A statistically significant area under the curve (0.940) and a very close projected omission line to an omission on training data verified an improved model run for Dactylorhizahatagirea. Our analysis confirmed the model's correctness with an AUC of 0.999. Table 1 shows omission rates and frequent criteria. When there are approximately 25 test samples, binomial probabilities are calculated correctly; otherwise, a common approximation is employed.

Both the null hypothesis (test points can be predicted) and the alternative hypothesis (random prediction with the same fractional predicted area) have one-sided p-values.

We multiply the following to get the ideal "Balance" threshold: training omission rate, cumulative threshold, fractional projected area, and 6.

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Table 1: Omission Rates at Various Prediction Thresholds for M. insignis Distribution

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training Omission rate	Test omission rate	P-value
1.001	0.000	Fixed cumulative value 1	0.036	0.009	0.040	4.583E-2
5.142	0.006	Fixed cumulative value 5	0.009	0.002	0.070	8.081E-3
10.050	0.029	Fixed cumulative value 10	0.003	0.010	0.006	1.569E-3
31.214	0.535	Minimum training presence	0.002	0.030	1.001	1E0
33.143	0.464	10 percentile training presence	0.080	0.020	1.003	1E0
31.342	0.663	Equal trainingsensitivity andspecificity	0.001	0.050	1.004	1E0
32.140	0.460	Maximum trainingsensitivity plusspecificity	0.000	0.001	1.002	1E0
17.472	0.380	Equal testsensitivity andspecificity	0.028	0.006	0.003	5.937E-4
17.466	0.340	Maximum testsensitivity plusspecificit	0.002	0.010	0.070	5.937E-4
1.262	0.002	Balance trainingomission, predictedareaand threshold value	0.037	0.022	0.011	3.718E-2
10.518	0.032	Equate entropy ofthresholded andoriginaldistributions	0.001	0.000	0.000	1.399E-3

Table 2 shows first estimates of environmental factors' model contributions. In each training cycle, the initial estimate is calculated by adding the increase in regularized gain to the relevant variable's contribution or removing it if lambda decreases. We randomly swap each environmental variable's training presence and background data variables in the second estimate.

Reevaluating the model using permuted data adjusts the percentage fall in training AUC. Bio13, the environmental variable that performed best in our investigation when used alone, seems to contain the most important information.

Table 2: Contribution of Selected Bioclimatic Factors to M. insignis Habitat Prediction

Bioclimatic Variable	Contribution (%)
Bio13 - Precipitation of wettest month	86.2
Bio18 – Precipitation of warmest quarter	3.8
Bio4 - Temperature seasonality	3.02
Bio14 - Precipitation of driest month	1.99
Bio2-Mean diurnal range	1.2
Altitude	1.5
Bio3 – Isothermality	1.0
Bio15 – Precipitation seasonality	0.92
Bio17 - Annual mean temperature	0.92

With its potential to provide the most unique insights not found in the other variables, the environmental variable altitute is the one whose removal has the biggest negative impact on the benefit. Similar to the jackknife, altitude, bio5 (Max temperature of warmest month), bio8 (Mean temperature of wettest quarter), bio9 (Mean temperature of driest quarter), bio10 (Mean temperature of warmest quarter), bio18 (Precipitation of warmest quarter), bio19 (Precipitation of coldest quarter), bio2 (Mean diurnal range), bio3 (Isothermality) are variables that had the least impact on the distribution model. On the other hand, bio13 (Precipitation of wettest month), bio16 (Precipitation of wettest quarter), bio15 (Precipitation seasonality), and bio12 (Annual precipitation) have a significant impact on the species model. Our findings are in line with previous research that has shown that weather conditions, including temperature and precipitation, significantly impact species distribution models. However, the most important factor influencing M. pulegium was found to be the coldest quarter's precipitation (Bio19). In alpine meadows, surface temperature influences plant growth and development, which in turn impacts plant distribution. Precipitation primarily influences surface temperature via the feedback mechanism of soil moisture, while air temperature is a direct factor that affects surface temperature. Precipitation is a major factor in plant dispersion, according to our results.

The results of the jackknife test for variable relevance. Bio13 seems to contain the most significant information on its own as it was the environmental variable that, when employed alone, produced the largest gain. Based on what we can see, Bio4 is the environmental variable with the greatest amount of data that is missing from the other variables. Relevance of variables was determined using the jackknife approach.

By training with each environmental variable first excluded and then utilized separately, this strategy eliminates variables one by one while the model is running. The practice of estimating species' geographic distributions using a limited number of occurrence or presence-only data has gained significant popularity in the ecology community. Among the environmental factors affecting the distribution of Nepatacrispa, elevation has the most impact, making up 26.4% of the model. Annual mean temperature (Bio1) and geography each contribute 19.% and 18.1%, respectively. If you know any limits on the unknown distribution, the MaxEnt approach can forecast it such that it has maximum entropy and meets all other requirements. A species's probability distribution reflecting the observed environmental constraints on the sites of existing species is the end product of the case study. Environmental variables, both continuous and categorical, and occurrence data from dispersed sample locations are all well-represented by the model. Since MaxEnt simply needs presence data, it has outperformed other models.

Because it only needs data about location and environmental factors, MaxEntmodeling is the way to go. According to other sources, MaxEnt is a useful tool for simulating endangered species, but the approach and data used to create the models determine how accurate they are. It is feasible to predict the future suitability and survival of a species using large-scale climate models, provided that its ecological niches do not undergo drastic changes to accommodate factors like climate or topographical changes. This is especially true for severely endangered species, such as M. insignis, which may have been unable to adapt to these changes and is now on the verge of extinction. This analysis takes into account two distinct SRES emission scenarios: A1: a rapidly expanding human population, massive energy consumption, and sluggish technical advancement; and B2: a medium-sized population, a variety of energy sources matching current consumption patterns. There are a number of climate models available at the moment, including HadCM3, CCCMA, and CSIRO. Out of all of them, HadCM3 was chosen for this research due to its history of producing superior mean findings for Asia. The range (2020–2080) was used to determine the possible climate change impacts. Based on the variation of models in relation to the current range, which was calculated by calculating range gained and range lost, we hypothesized that M. insignis would show a small increase in distribution across newer potential sites but would still be present in the current distribution sites after 60 years.

Future habitat conservation and species management efforts might benefit from climatic space forecasts for medicinal plants generated by a species distribution model. Several medicinal and endangered plant species have had their ranges reduced as a result of climate change. The species' distribution may alter regardless of whether the average regional occurrence probability remains unchanged due to climate change. The occurrence of geographic shifts is aggregated by calculating the likelihood at the pixel level in order to provide an indicator of species richness at each pixel.

Table 3: Field-Validated and Predicted Orchid Sites in Telangana with Coordinates, Population Estimates, and Herbarium References

S. No	Location	Latitude	Longitude	No. of Individuals	Herbarium No.
1	Kawal Wildlife Sanctuary, Nirmal	N 19° 07′ 25.3″	E 78° 46′ 12.6″	03	TNG2348
2	Eturnagaram Forest, Mulugu	N 18° 20′ 41.2″	E 80° 24′ 30.7″	02	TNG5364
3	Amrabad Tiger Reserve, Nagarkurnool	N 16° 04′ 10.5″	E 78° 56′ 45.1″	04	TNG5373

While these forecasts show some of the unexpected changes brought on by climate change, they also pinpoint more concentrated "hotspots" of transformation. For successful conservation or management measures, these predicted locations may need more in-depth research and focused field surveys. This research selected three readily accessible and highly anticipated regions to find new M. insignis populations, however only one or two individuals were identified at each site (Table 3). This confirms model-predicted distribution locations.

CONCLUSION

Ecological niche modeling was an important step in the right direction for evidence-based biodiversity protection when it came to determining where orchids were found in Telangana. Addressing information gaps in their geographical distribution, this work effectively identifies present and future habitats for orchid species by employing presence-only data and environmental factors. Orchids are ecologically delicate, and the results highlight how critical it is to protect their habitats from human activities and climate change. One proactive way to preserve orchid variety in the region is to use ENM with other conservation techniques including expanding protected areas, restoring habitats, and creating plans to reintroduce species. To ensure ecological and social resilience, this study emphasizes the need of local people, traditional knowledge, and sustainable management methods being part of conservation initiatives. The findings may help states with their conservation plans and add to the national biodiversity goals. Prioritizing the protection of orchids, a keystone group, is both an ecological requirement and a symbol of sustainable development as Telangana continues to urbanize and industrialize. Improving conservation efforts via the application of these scientific findings will need on-going research, stakeholder engagement, and policy interventions.

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