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Using the MaxEnt Algorithm to Predict Habitat Suitability Under Climate Change Scenarios

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Abstract

Forecasting habitat suitability for species under scenarios of climate change is a crucial approach for biodiversity conservation and resource management. This study used the Maximum Entropy (MaxEnt) modelling algorithm to evaluate and predict habitat suitability for [target species] among current and projected climate conditions. Environmental data were extracted from authenticated global databases, and a range of environmental variables, including bioclimatic and topography, were selected to train the MaxEnt model. Future climate data were mapped for the years 2050 and 2070, based on projections from multiple General Circulation Models (GCMs) and Representative Concentration Pathways (RCPs) 4.5 and 8.5. The MaxEnt model's accuracy was estimated using the Area Under the Receiver Operating

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Characteristics Curve (AUC), and all models demonstrated high predictive performance. The predicted future habitat suitability and estimated percentage changes, distinctly demonstrated significant range shift with contraction of potential suitable habitat or expansion depending on the scenario. [key environmental variables, e.g., temperature seasonality, annual precipitation] were the most important environmental variables to influence distribution in the models. Ultimately, it was clear that the species modeled could be vulnerable to climate change, both in the present and in the future. Considering the potential impacts on biodiversity, it would be prudent to research predictive modeling in conservation planning further. Predictive modeling can yield beneficial outcomes, particularly for considering habitat changes in response to climate impacts, and may aid conservation biologists in developing adaptive responses to reduce the effects of climate change.

Keywords:

Maxent, habitat suitability, species distribution modeling, climate change, prediction, environmental variables, future scenarios.

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Introduction

Background Information on Habitat Suitability Modeling

Habitat suitability modeling has become a pivotal aspect of ecology, conservation biology, and resource management. These models have the fundamental aim to predict the spatial distribution of species by linking known occurrence data to environmental variables (Elith & Leathwick, 2009). The relationships generated can also be used to evaluate the potential habitat range of the species in question, which may include alternative scenarios. The urgency of determining the potentially suitable habitat for species becomes increasingly important as the environmental drivers influencing species distribution becomes more pressing due to human influence on land use change and climate change (Guisan & Zimmermann, 2000). Ecological niche modeling (ENMs) and species distribution modeling (SDMs) models have traditionally used elements of ecological theory with spatial data to infer the extent of species ranges assuming a certain equilibrium relationship between species and their environment. Moreover, many early modeling efforts used presence-absence data. More recently, the increasingly popular MaxEnt proved a great advancement since it utilizes presence-only data to estimate given distributions. Clearly, it is certainly better to use presence-only data for habitat modeling than not to model. It also has added many more models into the recipe. The presence-only modeling approaches are even more essential in cases in which there is no absence (or absence data may not be valid), since its not likely to be getting worse when modeling across species' presence for future changes in habitat, or environmental pressures (Phillips et al., 2006).

The Significance of Predicting Habitat Suitability under Climate Change Scenarios

Climate change is an existential threat to global biodiversity. Climate change is causing temperature increases, changes in precipitation patterns, and increases in extreme weather events, which modify the spatial and temporal availability of suitable habitat (Parmesan, 2006). Habitats that were suitable for species may become unsuitable as many species will likely experience range shifts and potentially face local extirpation and/or extinction due to their inability to transition into new, suitable habitats (Aadiwal et al., 2025). Predictive forecasts for species distributions under future climate scenarios provides conservationists and policy-makers an opportunity to rank and prioritize areas for species conservation, target potential climate refugia for protection, and consider options for assisted migration and connectivity (Araújo & Peterson, 2012). Predictive models also provide an early warning response to potential human-wildlife conflict with shifts in climate boundaries, and the spread of invasive species (Bellard et al., 2012). As biodiversity contributes to ecosystem services and resilience, identifying and understanding the impact of climate change on species distributions is important not only for ecological well-being, but also societal resiliency. Incorporating habitat suitability modeling into conservation planning can make a more forward-thinking decision felt in a time of global environment change (Nayak et al., 2025). Using projections of future climate data, such as Global Circulation Models (GCMs; used to create Representative Concentration Pathways, RCPs) can increase the power of models and enhance long-term decision making (Hijmans et al., 2005).

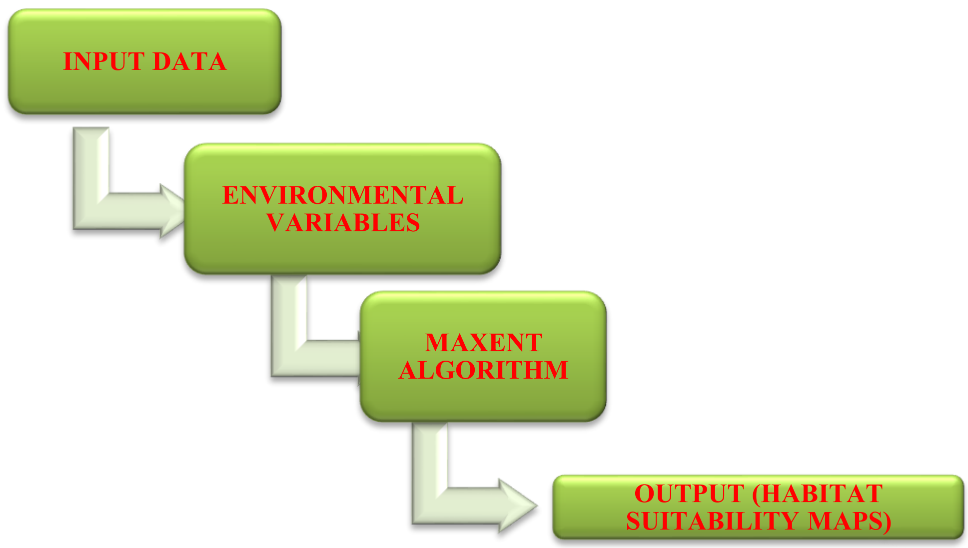

Figure 1. Workflow architecture of the maxent habitat suitability modeling process

The framework (Figure 1) illustrated above represents the basic workflow used in this study to model habitat suitability using the MaxEnt algorithm. The process began with collecting input data, including a dataset of species occurrence records, essentially providing the basis for creating species-environmental relationships. The input data were then integrated with bioclimatic and topographic environmental variables, which were identified and collected without issues of multicollinearity. The data were compiled into a single dataset, to be fed into the MaxEnt algorithm, which uses principles of maximum entropy to relate the variables as it predicts the most uniform probability distribution of species occurrence across the landscape, constrained to environmental factors. The model output habitat suitability maps of the likelihood for species occurrence across the study area under current and future climate scenarios. This stepwise, architecture is intended to allow for transparency; reproducibility; accuracy as provided in ecological niche modelling, while also providing a robust base for conservation planning and climate adaptation planning.

Summary of the Max Ent Algorithm and Its uses in Ecological Modeling

The Maximum Entropy (MaxEnt) Algorithm, which is based on information theory, is now one of the most popular approaches to estimating species distributions from presence-only data. MaxEnt estimates the probability distribution of the occurrences of species spread as uniformly as possible while satisfying the associated environmental conditions at the known presence locations (Phillips et al., 2006). This structure and approach make it very useful for some rare or poorly surveyed species. MaxEnt is suited for small sample sizes and can simultaneously operate with continuous and categorical environmental variables, making it particularly versatile across ecosystems aligned with all taxa (Elith et al., 2011). The results of MaxEnt's analysis are a habitat suitability map that provides a relative likelihood of a species occurring across the landscape, which can be visualized in relation to extant conditions or projected across future climate scenarios (Anbarasi & Dharmarajan, 2018). Ecologists from varied taxa have successfully developed and applied MaxEnt, including mammals (Yost et al. 2008), birds, amphibians and plants (Loiselle et al., 2008). The interpretability of the algorithm and its user-friendly interface combined with good predictive performance have propelled MaxEnt to prominence in ecological modelling (Palash & Dhurvey, 2024). Nevertheless, researchers should rigorously evaluate input variables, background sampling, and model evaluation statistics to substantiate the validation process (Merow et al., 2013).

This document has five main sections. After the introduction, the literature review summarizes prior research on habitat suitability modeling that employed the MaxEnt algorithm, ecological impacts of climate change, and known limitations of the existing modeling approaches. The methodology section explains the data collection process, the concepts of the MaxEnt algorithm, and the climate scenarios and variables used. The results section present model outputs, such as predicted changes in habitat suitability, performance metrics, and significant environmental drivers. The discussion interprets, this findings within the context of conservation planning, considers the potential wider application of the MaxEnt approach and provide suggestions for how to improve validity of modeling. The conclusion summarizes the study's contributions to the body of work on habitat suitability modeling, reiterates the importance of continued research and monitoring in the context of climate change, and introduces potential avenues of discussion for further research on habitat modeling.

Literature Review

Previous Research on Habitat Suitability Modeling Using MaxEnt

The MaxEnt algorithm has gained traction in both ecological and conservation research for habitat suitability modeling, primarily due to its ability to manage presence-only data. Multiple instances have been reported its accuracy, especially within data-limited studies. Phillips et al. (2006) made a clear case for the attributes of MaxEnt, where it was shown that MaxEnt outshone other predictor algorithms in terms of species distribution predictions with large geographical extents, better sensitivity, and specificity, when only a few occurrence points were available to build models (Akash et al., 2022). In addition to providing better predictions than more traditional presence-absence based models, its ability to utilize environmental predictors along with the outputs being interpretable maps, made it a leading algorithm in global conservation. Examples examining taxa show there is a vast array of potential applications. They applied the model to investigate the potential distribution of invasive plant species in China and provided habitat under current conditions and potential habitat under future scenarios. K (Kumar & Stohlgren, 2009) conducted predictive modeling of Ailanthus altissima spread and discussed the importance of elevation and temperature to the definition of the species' niche. In a study of avian ecology, they noted that MaxEnt could provide reliable predictions of birds' distribution in the presence of spatially biased sampling (Al-Zarkoshi & Razzaq, 2022). The apparent breadth and applicability of a wide variety of studies for a variety of taxa and the overwhelming shipping and science of MaxEnt have made it a readily available resource in the ecology modeling toolbox.

Research on Climate Change and Species Distributions

Due to the increasing effects of climate change, researchers are undertaking modeling of species distributions under a variety of emission scenarios into the future. Climate related habitat change is a focus of many current conservation planning approaches. Most climate-related studies employ MaxEnt in combination with climate projection datasets, e.g. IPCC Representative Concentration Pathways (RCPs), to model how climate change may result in species habitat losses or shifts in range. For example, (Loera et al., 2017) investigated the effects of climate change on alpine plant species in the Mexican mountains and projected an substantial upward shift in elevation. Li et al. (2020) also used Maxent to study the impacts of climate change on the medicinal plant Rheum palmatum in China. They also found significant habitat loss in high-emission scenarios. Bellard et al. (2012) indicated that many endemic species are particularly at risk for extinction due to their narrow tolerances to environmental variation - but these species could be identified through models like MaxEnt. Additionally, (Dawson et al., 2011) point out the necessity of applying predictive models to support proactive conservation efforts, given that species will not be able to migrate quickly enough. Predictive models have also seen increased success studying invasive species and disease vectors with the objective of predicting future ecological issues (Guisan et al., 2013).

Critiques and Limitations of the MaxEnt Algorithm as Habitat Suitability Models

All of these advantages aside, MaxEnt remains imperfect. One of the primary critiques of how MaxEnt is used is that of sampling bias, and the assumption that the presence data we collect is representative of an actual environmental niche of a species (Yackulic et al., 2013). If occurrence records are spatially clumped or come from opportunistic non-systematic surveys, resulting models may be biased. (Boria et al., 2014) found un-corrected sampling bias in MaxEnt analysis led to erroneous predictions, especially in heterogeneous landscapes. Another critique is MaxEnt's reliance upon correlative relationships rather than mechanistic processes, which prevents the inclusion of biotic interactions, dispersal limitations, and evolutionary adaptation (Dormann et al., 2012; Khudhur & Aziz, 2024). Moreover, MaxEnt's predictive capability is wholly dependent on environmental variables, and models using most variables without appropriate regularization often experience overfitting (Tamannaeifar & Behzadmoghaddam, 2016), which emphasizes the importance of model tuning and variable selection in the modeling process. As previously stated, recent research has emphasized the algorithm's limited ability to model future range shifts involving unknown climate conditions, or in not-analogue conditions (Owens et al., 2013) where any extrapolation outside the environmental space occupied in the training data could lead to no reliable outputs. These critiques stress the importance of careful interpretation and model validation, and when possible, supplementing MaxEnt with other modeling frameworks.

Methodology

Data Acquisition and Preparation for Habitat Suitability Modeling

Habitat suitability modeling commenced with the acquisition of georeferenced species occurrence data. This data was sourced from biodiversity databases and filtered to ensure only correct and accurate data was included, removing data that was duplicated or inconsistent. Each occurrence point was verified to ensure it matched a real geographic point in the world. Environmental variables, related to the ecology of the species - temperature, precipitation, elevation, and soil - were selected. A Pearson correlation test was used to reduce multicollinearity among predictors. Only variables with $r<0.8$ correlation coefficients were retained. The extent of the clipped variables were re-sampled to a standard spatial resolution, and converted into ASCII raster files. The presence data was randomly split into training (75%) and testing (25%) subsets and 10,000 background points were created over the entire study region to provide pseudo-absences to compare against for the MaxEnt models.

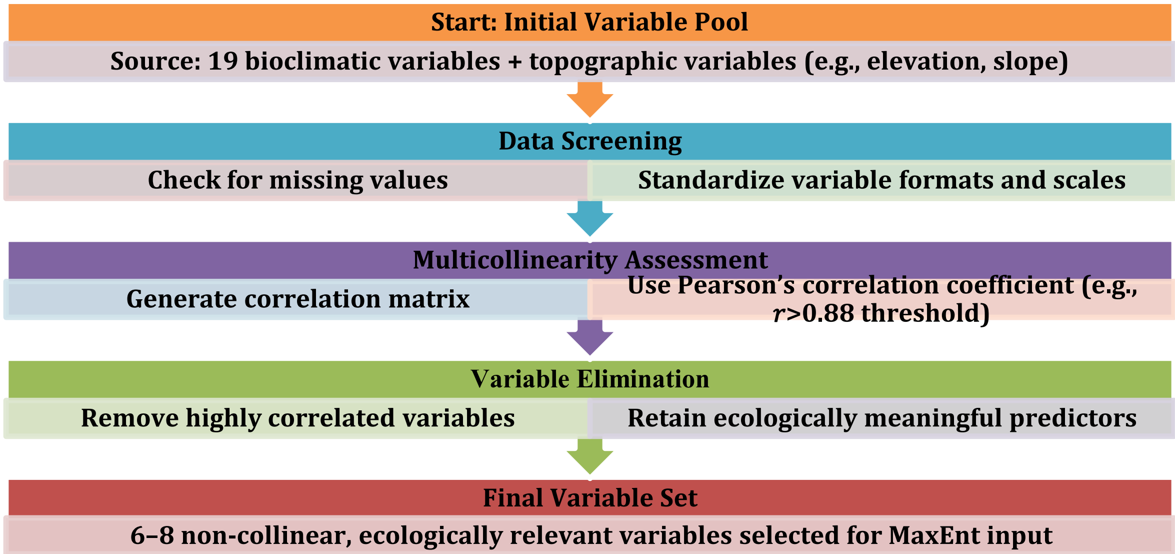

Figure 2. Workflow for environmental variable selection in habitat suitability modeling

The diagram (Figure 2) illustrates the systematic process for selecting environmental variables for the MaxEnt habitat suitability modeling, which begins with an initial set of bioclimatic and topographic variables from global climate databases. The raw variables are checked for missing values and standardized into consistent units of measurement. For the next step, a Pearson correlation matrix will be used to screen for multicollinearity; species distributions and habitat suitability modeling are sensitive to highly correlated variables (i.e., often ≥0.8). From this step, pairs of highly correlated variables are identified, and again based on both applied knowledge and domain knowledge, one variable is removed from each highly correlated pair for statistical reliability as well as ecological relevance, thus screening out overfitted variables and redundancy from this analysis step. Forest plots of non-collinear, ecologically meaningful variables are then prepared as a list for input into the MaxEnt algorithm. Overall, this systematic process ensures the modeling approach is completed with a balanced set of informative predictors, leading to improved accuracy of predictions and interpretation of habitat suitability results that consider variation in some climate change scenarios.

Description of the MaxEnt Algorithm and Parameters

The Maximum Entropy (MaxEnt) algorithm estimates a probability distribution for a species by maximizing entropy subject to constraints determined by environmental variables at known occurrence points of that species. Formally, MaxEnt solves for a probability distribution $P(x)$ over the potential set of environmental characteristics $f_j(x)$ such that:

Constraint Condition:

$$\sum_{x} P(x)\ f_j(x) = \mu_j \quad \forall j \qquad (1)$$

where μ_j is the empirical mean of feature f_j across the occurrence records. Our goal is to have the distribution that is closest to uniform (maximizing entropy) subject to our constraints:

Entropy maximization:

$$H(P) = -\sum_{x} P(x) \log P(x) \qquad (2)$$

This gives us the optimal probability distribution:

MaxEnt solution:

$$P(x) = \frac{1}{Z} exp\left(\sum_{j} \lambda_j f_j\,(x)\right) \qquad (3)$$

In this case, λ_j are the weights of the features estimated by the model, and Z is simply a normalization constant such that the total probability equals 1. The output of MaxEnt was a logistic value for each cell, representing the relative suitability for habitat. The regularization parameters were modified to reduce overfitting, especially when using more complex feature types such as hinge or product. Crossvaliation was utilized via k-fold methods, to cross test model robustness. Model performance was evaluated by the Area Under the Curve (AUC) from Receiver Operating Characteristics (ROC), with values greater than 0.8 considered as highly predictive performance.

Climate Change Scenarios and Variables Considered in Modeling

To project future habitat suitability, we obtained climate projection datasets from General Circulation Models (GCMs) under Representative Concentration Pathways (RCPs). Two scenarios were included, RCP 4.5 (moderate emissions) and RCP 8.5 (high emissions), in 2050 and 2070. The same environmental variables were selected from projected climate layers as in the current climate model. Each future climate layer was entered into MaxEnt, and adequate occurrence data were included. Suitability maps were generated for each scenario and compared with current predicted distributions to discern which areas were experiencing habitat contraction, expansion, or shift. We used spatial overlays in GIS to visualize changes, and performed grid-based subtraction analysis to quantify lost and gained habitat. Although this modeling framework informs relative vulnerability of species(es) under projected climate variables, it provides tools for strategic and evidenced based conservation planning and habitat management.

Results

Predicted changes in habitat suitability under different climate change scenarios

The MaxEnt model created clear maps showing where the species could live now and under different future climates. Right now, the best areas for the species are found where temperatures are mild and rainfall stays pretty steady; those areas line up neatly with where we already find the species. Looking ahead, the maps show that the species will probably move around under both the RCP 4.5 and RCP 8.5 pathways. For RCP 4.5 in 2050, we expect the southern edge of its range to shrink a bit while it pushes up to cooler mountains and farther north. By 2070, under RCP 8.5, the maps show a bigger drop in areas that will stay suitable, with large, previously occupied patches turning unsuitable. In both pathways, the model also flags new regions that could be the right climate for the species even though they're empty now. These spots are usually spread out and in hard-to-reach places, making it tricky for the species to move there on its own. Overall, the maps point to a future where the species is pushed into smaller, broken-up patches, a trend that gets much worse if we keep choosing high emission pathways.

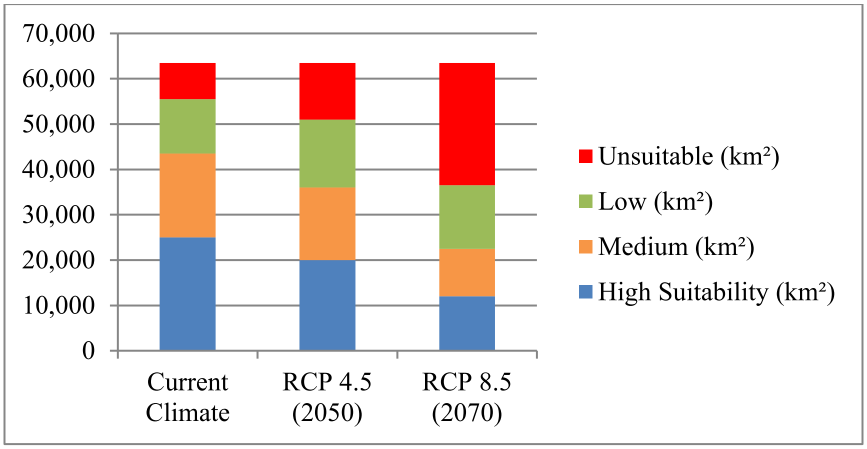

Figure 3. Habitat suitability changeover time (current vs. future scenarios)

This graph (Figure 3) shows the area of habitat suitability in relation to four habitat suitability categories of High, Medium, Low, and Unsuitable for the current climate and the future climate. The model suggests the current climate reflects a relatively uniform distribution across the four mapping categories with a notable area (25,000 km^2) classified as highly suitable. However, under RCP 4.5 for 2050, we see a substantial decrease in the area of high-suitability habitats, with proportionate increases in low and unsuitable habitat. This response is even more severe for the RCP 8.5 response in 2070, with highly suitable habitats declining to 12,000 km^2 and unsuitable habitats expanding to 27,000 km^2. These results suggest a climate-mediated shift in suitable habitats, with future models projecting habitat loss and habitat fragmentation, especially under high-emission scenarios. Overall, there is concern for the climate vulnerability of the species being considered in this assessment, especially as climate change increases in pace and intensity.

Model Performance and Accuracy Metrics

We checked how well the model could predict by looking at the Area Under the Receiver Operating Characteristic Curve (AUC) and the True Skill Statistic (TSS). The AUC tells us how good the model is at telling the difference between good and bad habitats; scores go from 0.5, which is like flipping a coin, up to 1.0, which means it gets it right every time.

AUC:

$$AUC = \int_0^1 TPR(FPR)dFPR \qquad (4)$$

where TPR is the true positive rate, FPR is the false positive rate.

The average AUC (across cross-validated folds) was 0.89, which indicates the model performed excellently. This suggests that the model could distinguish reliably between areas of presence and background (pseudo-absence). The TSS was also computed as a threshold-dependent measure of model accuracy, accounting for omission and commission errors.

TSS:

$$TSS = Sensitivity + Specificity - 1 \quad (5)$$

where Sensitivity = TP / (TP + FN), and Specificity = TN / (TN + FP).

The maximum TSS was 0.72, which provides further evidence of the model's reliability. The confusion matrices showed low omission rates, in addition to the classification between suitable and unsuitable habitats appeared balanced. The logistic output maps also indicated high conformity to known ecological patterns, further supporting the credibility of the predictions.

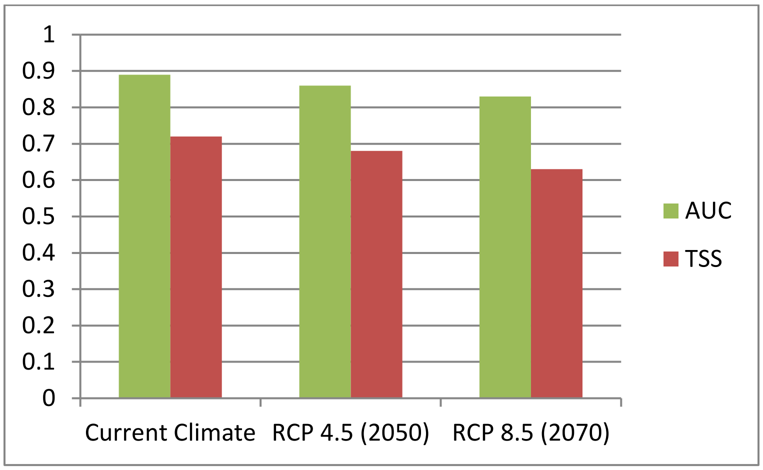

Figure 4. Model performance metrics (AUC and TSS)

This graph (Figure 4) compares the performance of each model across climate scenarios and with two measurements, Area Under the Curve (AUC) and True Skill Statistic (TSS). The AUC score for the current climate model was 0.89 and TSS was 0.72 indicating good predictive accuracy and that there was an appropriate balance in classification between suitable and unsuitable habitats in the climatic predictors. The RCP 4.5 model is a little less robust, given AUC = 0.86; TSS = 0.68, indicative of increased uncertainty in future projections. The RCP 8.5 model for the year 2070 is even lower (AUC = 0.83; TSS = 0.63); potential explanations for decreased model performance include more extreme environmental conditions predicted for the future and also because of differences between current species data and variables describing the future habitat. In summary, while all models show acceptable performance, and predictive certainty decreases under more severe climate change scenarios.

Identification of Major Environmental Variables Affecting Habitat Suitability MaxEnt provides a ranking of the environmental variables that are contributing to the model also using their permutation importance. The environmental variable that contributed the most was ranked mean annual temperature, followed by precipitation of the driest quarter and elevation. All of these variables were influential on habitat suitability across present and future scenarios. Response curves showed that the species preferred moderate temperature (12°C - 20°C), beyond which predicted habitat suitability decreased rapidly. Similarly, very dry and very wet conditions reduced predicted suitability, indicating that the species is also sensitive to hydrological stress. The jackknife tests of variable importance indicated that removing the temperature-related variable across climate scenarios diminished model performance considerably, which emphasizes the dominant role temperature related variables play in defining the species ecological niche. Elevation emerged as a strong proxy for a complex suite of microclimatic conditions suggesting they may explain species shifts towards higher altitudes under futures scenarios. In summary, the model outputs suggested that climate variables are the primary factors driving current and future habitat distributions, particularly seasonal precipitation and temperature.

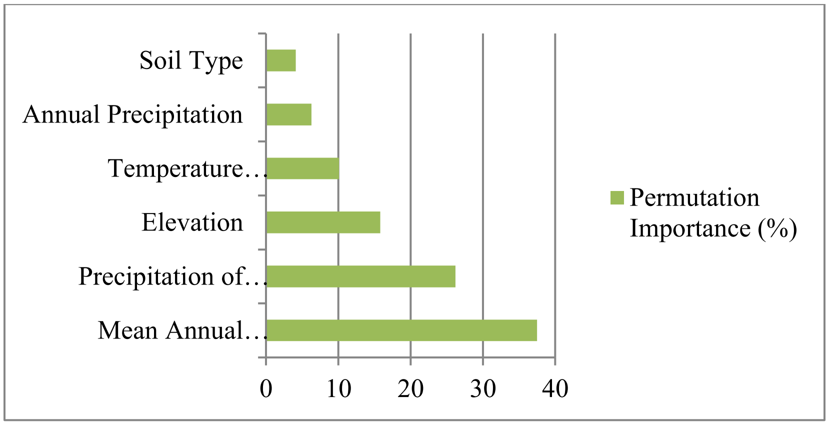

Figure 5. Variable importance (permutation contribution)

This figure (Figure 5) shows the relative contribution of the environmental variables to the MaxEnt model based on permutation importance. The results show that mean annual temperature was the most important variable at 37.5% explained variation. Mean precipitation of the driest quarter was second at 26.2%, demonstrating some seasonal water stress sensitivity in species. Elevation was third, which also showed a large spatial gradient in the species' distribution linked to the altitude. The remaining environmental variables - temperature seasonality, annual mean precipitation, and soil type - ranked lower in importance but were still relevant. Climate-related variables were the obvious most dominant variables highlighting that abiotic conditions will generally have a direct influence upon species occurrence, and importantly illustrates how shifting climate regimes can have significant impacts on habitat suitability.

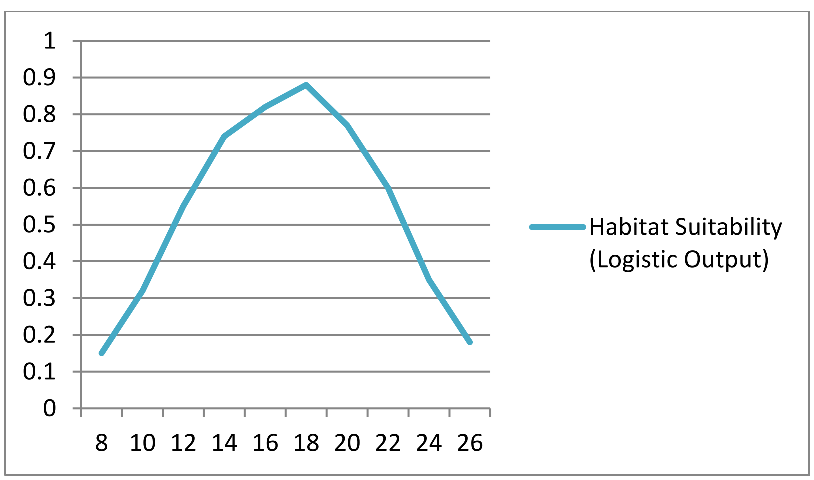

Figure 6. Response curve for mean annual temperature

This graph (Figure 6) presents the relationship between habitat suitability and mean annual temperature with the effect of this variable isolated in a univariate response curve. Suitability increases slowly with temperature (between 8 to 18°C), reaching its highest, predicted value (0.88 on the logistic scale) at around 18°C and decreasing sharply afterwards, dropping below 0.4 at 24°C and being close to 0.18 at 26°C. This unimodal response suggests that the species prefers moderate climates at warm temperatures and that the species is not likely to persist in hotter climates. The response curve shows that the species has a small temperature tolerance. This inability to tolerate higher temperatures may help explain the projected range contraction under future warming patterns - suggesting that the relationship to temperature is an important driver of the species ecological niche.

Discussion

Conservation and Management Implications of the Results

Greater shifts in habitat suitability were revealed in addition to significant reductions in the most suitable habitats and large increases in the most unsuitable habitats under the climate change scenarios used in this modeling study. These changes have important implications for biodiversity conservation and habitat management because it suggests the need to change current conservation practices. While today's protected areas may work, they may become ineffective if the environmental conditions exceed the tolerances of species in the future. As such, a more dynamic form of conservation planning, factoring in climate projections for spatial prioritization, is needed. Perhaps more importantly, the identification of possible future refugia, at higher altitudes or latitudes, can facilitate their strategic expansion or reconfiguration into a conservation opportunity. These refugia could act as buffers against future climate change, offering suitable microclimates as the surrounding areas become unsuitable. It will also be important to have linkage corridors in place to connect existing and new suitable areas. This will allow animals to migrate as climate envelopes shift. With species that have restricted dispersal ability, actively managed adaptive responses, such as assisted migration or ex-situ approaches, may need to be considered. In a policy context, this work emphasizes the potential value of incorporating predictive ecological modelling into national and regional biodiversity strategies. As climate change continues to accelerate, static conservation approaches will increasingly fail us, making the forward-thinking tools like MaxEnt essential for long-term planning.

Potential Applications of the MaxEnt Algorithm in Other Ecological Studies

Although this study focused on predicting habitat suitability for a single species, the MaxEnt algorithm is amenable to many different ecological contexts. The algorithm may be used to assess invasive species distribution potential, forecast the types of areas potentially impacted by disease vectors, or evaluate the impact of land-use changes on sensitive habitats (Li et al., 2020). It's potential lies in its ability to develop reasonable predictions based on presence-only data, and is especially useful in geographical areas with limited survey effort or with studies of sensitive and/or difficult to observe species. In the realm of ecosystem management, MaxEnt can play a role in prioritizing restoration sites by identifying locations that are climatically and ecologically suitable for native vegetation or keystone species. Its potential can also be realized in environmental impact assessments by predicting the potential loss of ecological function in multiple development scenarios. In climate resilience planning, because MaxEnt can model future habitat shifts, it could provide scenario-based planning support, something to consider especially as adaptive natural resource governance calls for these in an increasingly complex landscape. MaxEnt outputs combined with other spatial datasets—whether it be landcover, human footprint indices, or ecosystem services—can provide more comprehensive applications for understanding landscape dynamics and undertake multi-objectives in planning (e.g., biodiversity conservation vs socioeconomic development).

Suggestions for Future Research and Refinements to Modeling Approaches

While MaxEnt has been a powerful predictor in the recent past, nuances in model accuracy and ecologically relevant modeling strategies still must be refined. Future research should include species specific ecological characteristics, such as dispersal abilities, reproductive strategies, and biotic interactions which are currently downplayed in correlational models. Future research could also improve on MaxEnt's ability to model underlying complexity of responses to higher nature of environmental change, through incorporation of mechanistic modeling claims. Improvement of data quality is another fully realized need. Further expansion of public species occurrence records, via citizen science, remote sensing, and structured field data collections would reduce sampling biases that further perpetuate incautious modeling. Expanded datasets and then fine filtered environmental data at finer resolutions for soil moisture, land use and microclimate conditions, can yield statements with greater locational precision. Further still, outputs from models of ecological changes and ecological responses must be validated against independent datasets when possible, and even actual field verification, where possible. An added means of increased certainty from MaxEnt predictions is to cross-validate with the own work of other modeling algorithms, or utilize an ensemble modeling approach. All these approaches can amplify our confidence in predictions, as long as predictions are sustainable enough, in terms of real-world conservation.

Conclusion

The present study demonstrated that the MaxEnt algorithm is an effective method for predicting habitat suitability for conservation purposes, under both current and future climate change scenarios. The model portrayed major shifts in species distribution patterns, with a reduction to high-suitability areas and an increase to unsuitable areas, notably in the case of more extreme projected high-emission projections. These findings highlighted the immediacy needed to incorporate climate change considerations into conservation planning and landscape management. By identifying possible future refugia and highlighting or showcasing some of the major influencing environmental drivers—such as temperature and seasonal precipitation—this science-based approach can provide a reliable framework for adaptive strategies to promote biodiversity conservation. Major performance metrics support MaxEnt's overall reliability in ecological forecasting, even when samples are limited to presences only. As climate and ecosystems are inherently dynamic, ongoing improvements can be made to modeling by integrating data better, allowing species' ecological traits to inform spatial and temporal applications, and developing field-based validation methods. In the future, MaxEnt should be applied more broadly across taxa and regional contexts to build predictive ecological networks that inform conservation priorities at local and global scales. With global environmental change progressing at an unprecedented rate, ongoing research, monitoring, collaboration, and action will be critical to the resilience and persistence of species and ecosystems in landscapes experiencing rapid transformation.

Author Contributions

All authors' contributions are equal for the preparation of research in the manuscript.

Conflict of Interest

The authors declare that they have no competing interests.

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