

Impacts of climate change on the distribution of Critically Endangered *Saurauia punduana* in Northeast India

Puranjoy Mipun

Bhattadev University

Kuladip Sarma

Gauhati University

Jintu Sarma

dr.jintusarma@gmail.com

Guwahati College

Deiji Narah

Joya Gogoi College

Baby Doley

DDR College

Bijay Singh Mipun

Assam Royal Global University

Research Article

Keywords: *Saurauia punduana*, Critically Endangered, Maxent model, Weighted Overlay, East Karbi Anglong wildlife sanctuary

Posted Date: June 26th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9838203/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

The potential habitats of *Saurauia punduana* Wall. (Actinidiaceae) – a Critically Endangered (CR) tree species of Northeast India has been elucidated and through delineating and characterizing the predicted habitat, conservation strategies have been recommended. Modelling of the distribution of its potential habitats using machine-learning tools i.e., ensemble model (maxent and random forest) for the current climatic scenario as well as for two future climate scenarios for the year 2060 has been done. The model calibration test for *S. punduana* yielded AUC_{train} value of 0.959 with a kappa value of 0.446 indicating an excellent performance in the current climatic scenario. Likewise, the two future climate scenarios studied have also shown high performance in the modelling having AUC values more than 0.90. The ensemble model for the SSP5-8.5 scenario under CMCC model revealed that only 2.88% of the total area of NE states will be left as very high suitable area for the species. The identified areas may help guide programmes for rehabilitation, reintroduction, conservation and perpetuation of such critically endangered species in their natural habitat.

Introduction

One of the major contributors to the global biodiversity problem has been recognized as habitat loss, which has deleterious effects on community structure, functional diversity, individual fitness, and species richness (Roy 2022). Removal of natural vegetation has profoundly altered the natural landscapes leading to a decline in the habitat quality and native plant species population (Kumari 2022; Hansen et al. 2013). Such degradation coupled with other large-scale exogenous disturbances such as climate change has brought more than 20% of the global plant diversity to the brink of extinction (Brummitt and Bachman 2010). Currently, the majority of the native species populations are concentrated in and around nature reserves, wilderness areas and protected areas (Corlett 2016). Such areas cover only ~ 14 percent of the global land surface area, of which about 32.8 percent area is already experiencing various forms of anthropogenic disturbances (Jones et al. 2018). Also the State of the World's Plants and Fungi Report 2020 estimates that nearly 40% of global plant species are at risk of extinction. In Northeastern India, climate change is likely to have a significant negative impact on several endemic and threatened plant species, including *Vatica lanceaefolia*, *Nepenthes khasiana*, *Coptis teeta*, *Amentotaxus assamica*, *Illicium griffithi*, and *Taxus wallichiana*. (Bhuyan et al. 2025; Bhuyan et al. 2025; Sarma et al. 2024; Tiwary et al. 2024). In addition to habitat degradation and over-extraction of resources, introduction of invasive species continues to be a key factor in threatening the global loss of native species (Rai and Singh 2020). The loss of native plant diversity can directly affect the environmental quality as it acts as sink for air pollutants (Shackleton et al. 2019; Rai and Singh 2020). Moreover, climate change has further complicated the downstream effect on species conservation, leading to local or global species extinction events. This highlights the importance of predictive tools for quicker assessment of priority species.

Contemporary conservation programs primarily focus on designing reserve networks for *in situ* conservation and legal protection of the extant plant diversity (Williams and Araujo 2000; Araujo et al.

2002; Ferrier 2002; Cabeza et al. 2004). Nevertheless, adopting appropriate species-specific conservation and population rehabilitation demands a profound understanding of various ecological factors governing their distribution (Menges 1991). In this context, modelling the ecological niche and potential areas substantially improves our understanding of the ecological requirements and distributional patterns of plants (Adhikari et al. 2012, 2018). Particularly, habitat distribution modelling helps in making reasonable inferences about the potential restoration sites under different environmental scenarios and helps in the identification, delineation, and prioritization of areas for conservation (Zimmermann et al. 2010; Borthakur et al. 2018).

Until now, substantial technological advancements have been achieved on the means of collection, processing and storage of environmental data (Johnson 2007; Kelling et al. 2009; Michener and Jones 2012). However, incorporating diverse modelling methods and environmental datasets in a common framework to elucidate and test a given ecological hypothesis is a major challenge (Austin 2002; Huston 2002; Wiens 2002). For example, the researchers employ a variety of environmental variables as well as modelling methods having different levels of complexity (Guisan and Thuiller 2005; Tsoar et al. 2007). Models generated through such contrasting methods vary depending on the type of environmental data e.g., satellite-based or interpolated climate surfaces, sample size, and complexity of parameterization leading to spatial incongruity in predictions (Guisan and Thuiller 2005; Hernandez et al. 2006; Evans 2012). However, here the silver lining may be that areas of spatial congruities identified through spatial overlays of predictive models generated through contrasting methods may help in delineating potential habitats facilitating efficient and inclusive decision-making (Thuiller and Münkemüller 2010).

Saurauia punduana is native to India (Assam), Bangladesh, East Himalaya, Myanmar and Tibet (POWO 2025). The species have a diverse range of habitat, but the population of the species is declining day by day due to various anthropogenic activities. It is included in the Red List of threatened species as per the assessment of the China Plant Specialist Group (IUCN 2020). *Saurauia* plant has prominent medicinal importance as it has been widely used to treat a variety of diseases traditionally and is found to have various biological activities such as antioxidant, anti-cholesterol, antidiabetic, antihyperlipidemic, analgesic, antimicrobial, wound-healing activity and immunostimulatory (Pasaribu et al. 2020).

As per report, it has several therapeutic uses that highlight its importance in traditional medicine and health practices (Chanda and Mukherjee 2012; Dobriyal and Dobriyal 2014; Deb and Gangmei 2017). The species faces significant threats to its survival, similar to many other species in the Northeastern region of India, due to various anthropogenic activities and disturbances in their natural habitat that have significantly impacted their population (Mir et al. 2022).

The economic importance of *Saurauia punduana* is noteworthy, as it has been recognized as a valuable non-timber forest product with significant market potential. The gum exudate of the closely related species, *Sterculia urens*, has a high market value, suggesting that *Saurauia punduana* could similarly become a lucrative source of natural gums or resins (Chanda and Mukherjee 2012). These could be utilized in industries such as pharmaceuticals, food, and cosmetics. Moreover, flower buds and fruits are

taken as food and the young leaves are used as a vegetable for building immunity (Dobriyal and Dobriyal 2014).

In the present study, we elucidate that an ensemble model of current and future climate scenarios can help in identifying the potential areas for conservation and reintroduction at a local scale. We expound this by modelling the potential habitat distribution of *Saurauia punduana* Wall. (Actinidiaceae) - a critically endangered tree species of northeast India in the East Karbi Anglong Wildlife Sanctuary (EKAWLS).

Materials and methods

Study area and study extent

We conducted survey in the East Karbi Anglong Wildlife Sanctuary (EKAWLS) of Assam in northeast India (Fig. 1) for enumerating population status of the taxon. The sanctuary covers an area of 221.81 km² and is an important component of the Karbi Anglong-Kaziranga landscape and Kaziranga-Karbi Anglong Elephant reserve in the Indo-Burma biodiversity hotspot (WWF 2002). It is situated between 24°33' N to 26°35' N Latitude and 92°10' E to 93°50' E Longitude and is 80–700 m asl. The topography of the study site ranges from undulating hills to wide valleys and steep gorges with rivers and creeks, as well as annual and perennial streams. The soil is well-drained, sandy loamy to clayey loamy. The climate is warm and humid with an annual rainfall of 1800 mm. The average maximum temperature is around 30°C in August, and the minimum goes down to 6.5 °C in winter. The wildlife sanctuary holds different forest types ranging from moist semi-evergreen, moist mixed deciduous to miscellaneous type with scattered pure or mixed patches of bamboos. The sanctuary is very rich in biodiversity with both native flora and fauna. Some of the prominent tree species found in the sanctuary are Hoong (*Dipterocarpus macrocarpus*), Mekai (*Shorea assamica*), Nahar (*Mesua ferrea*), Sissoo (*Dalbergia sissoo*), Khair (*Acacia catechu*), Helika (*Terminalia chebula*), etc.

Moreover, the location information of the study taxon was collected from various poackets of Northeastern states of India to be used in the model (Table1). Northeast India was taken as the extent of the model as the species distribution is known for the region and distribution records were collected form this region.

Study species

Saurauia punduana Wall. is an evergreen medium-size tree upto 6 m tall. Leaves abaxially tomentose, oblanceolate-obovate, 10–40 × 5–15 cm, base obtuse to cuneate, apex acute to abruptly short acuminate. Inflorescences axillary cymes or fascicled on young branchlets, with scattered scales, bracteate; Flowers pinkish white with scaly and densely tomentose; stamens numerous; Fruit berry, globose ovoid; seeds numerous, brown. (Fig. 2 & 3). *S. punduana* was collected from the East Karbi Anglong Wildlife Sanctuary and examined by P. Mipun (Voucher No. NEHU-12948). The specimen was authenticated by Dr. Dilip Kumar Roy and deposited in the NEHU Herbarium under Voucher No. NEHU-12948.

Population survey in EKAWLS

To record the current existing population status, a wide range of repeated field survey was made from the years 2018 to 2020 to locate the species. Total population of the species was ascertained through direct count of all the individuals, considering saplings (>1 m height) and matured individuals (≥ 1.5 m height). The coordinates of the occurrence localities were determined using a Garmin global positioning system (GPS) device to an accuracy level of ~ 5 m. The number of individuals of adult trees, saplings and seedlings for *S. punduana* in each location were determined through direct counts.

Distribution Modelling Approach

To model the species distribution, an ensemble approach was applied using the ensemble model function of the SSDM package in R (Schmitt et al. 2017). This approach combines the outputs of multiple models to provide a more robust and accurate prediction of species distribution. The ensemble modelling technique is known for reducing the uncertainty associated with individual model outputs and improving overall prediction accuracy. For developing the both current and future climate model, the same function and package has been used using the following algorithms-

Two algorithms were employed for the classification:

Maxent: A machine learning method commonly used for species distribution modeling that estimates the distribution of a species based on presence-only data. Maxent is well-suited for handling complex interactions between variables and performs well with limited presence data.

Random Forest: An ensemble learning method that uses multiple decision trees to improve prediction accuracy and reduce overfitting. Random Forest is a versatile and powerful algorithm for classification tasks, capable of handling both categorical and continuous data.

The ensemble model combines the outputs of these two algorithms to generate a final, integrated species distribution prediction.

Occurrence data

A total of 36 geographic locations collected from the various parts of Northeast India have been used in the model as dependent variables. These locations were primary data collected during the field survey from January 2018 to December 2020 and locations were recorded through handheld GPS.

Predictor Variables

The model utilized 19 bioclimatic variables, elevation data, and three soil parameters in two depths (5 cm and 15 cm) as predictors in the current distribution model. However, for future climatic models, only the bioclimatic variables were chosen as available in the database under the model CMCC-ESM2, a component of the Coupled Model Intercomparison Project Phase 6 (CMIP6). Two distinct Shared Socio-economic Pathways (SSPs)-namely SSP2-4.5 and SSP5-8.5-for the periods 2041-2060. According to the

SSP2-4.5 scenario, reasonable steps will be done in the future to cut emissions and prepare for climate change. It is predicated on balanced environmental and social policies, consistent population growth, and technology improvements. Despite some implementation issues, international collaboration finally causes greenhouse gas emissions to stabilize, even though they continue to climb throughout the twenty-first century (O'Neill et al., 2014). On the other hand, the SSP5-8.5 scenario depicts a future with high emissions and little adaptation. According to this scenario, emissions will continue to rise as a result of poor environmental controls, rapid population growth, and rising energy demand. This path represents a world that is having difficulty addressing climate change due to a lack of international cooperation and insufficient climate action (Riahi et al., 2017). These variables were chosen based on their relevance to species distribution and their availability from reliable global databases. Details of the predictors are described below-

Bioclimatic Variables: Nineteen bioclimatic variables at a resolution of 30 arc-seconds were obtained from the WorldClim database (<https://www.worldclim.org/>). These variables represent different aspects of climate, including temperature and precipitation patterns. The WorldClim dataset provides high-resolution global climate data, which is commonly used for ecological modeling.

Soil Parameters: Soil data was sourced from the SoilGrids database (<https://soilgrids.org/>). The soil parameters included soil organic carbon content, soil pH, and soil texture (sand, silt, and clay percentages), which are critical factors influencing species occurrence and distribution.

Elevation Data: Elevation data was also incorporated into the model as an important environmental variable influencing species habitat. The elevation DEM (Digital Elevation Model) was also downloaded from Worldclim database (<https://www.worldclim.org/>) at a 90-meter spatial resolution.

Data Processing

The bioclimatic and soil datasets were downloaded and processed to match the study region's spatial extent and resolution. All predictor variables were resampled and aligned to ensure consistency in spatial resolution, enabling accurate analysis and modeling. The bioclimatic and soil data were imported into R using the appropriate libraries, and pre-processing steps such as cropping, masking, and rescaling were carried out to prepare the data for modeling.

Model Development

The species presence data was compiled and input into the SSDM package, where the ensemble model was built using the ensemble model function. This function integrates the results from both Maxent and Random Forest algorithms. Model tuning was performed to optimize the parameters for both Maxent and Random Forest models. The output from each algorithm was combined in the ensemble model to increase prediction accuracy and reliability.

Model Evaluation

The model's performance was evaluated using various statistical metrics such as: Validation of the model was conducted using 10-fold cross-validation, and the performance of the models have been assessed through the area under the receiver operating characteristic (AUC) curve and the True Skill Statistic (TSS). 75% of the species occurrence data was used as the training dataset for model building, while the remaining 25% was used as the test data. To determine the best-fitting model and generate the ensemble probability surface, an AUC threshold of <0.75 was set. Validation of the final ensemble model relied on AUC values derived from the Receiver Operating Characteristic (ROC) curve, with model performance categorized into four tiers: poor (0.0-0.7), average (0.7-0.8), good (0.8-0.9), and excellent (0.9-1.0) (Johnson et al., 2016)

AUC (Area Under the Curve): AUC is a measure of the model's ability to discriminate between presence and absence locations. Higher AUC values indicate better model performance.

Kappa Statistic: The Kappa statistic measures the agreement between predicted and observed species distributions while correcting for random chance.

By employing these evaluation metrics, the performance of the ensemble model was assessed, and its effectiveness in predicting species distribution was confirmed.

Model Output

The final output from the ensemble model is a species distribution map showing the predicted occurrence and habitat suitability for the species across the study area. The ensemble approach, combining Maxent and Random Forest algorithms with multiple environmental predictors, provides a comprehensive understanding of the species' ecological requirements and its potential distribution range.

Mapping the distribution of potential habitats in current and future climate

The final mapping of the model outputs was done using Arc Map 10.2 version and the area statistics were calculated separately for current and future climate scenario.

Results

Population status

S. punduana was present in 17 localities in the EKAWLS. Overall, 72 individuals comprising of 10 seedlings, 18 saplings and 44 adults were enumerated during the entire study period.

Ensemble model and habitat suitability

The model calibration test for *S. punduana* yielded AUC_{train} value of 0.959 with a kappa value of 0.446 indicating an excellent performance (Fig. 3; Table 1) in the current climatic scenario. Likewise, the two future climate scenarios studied have also shown high performance in the modelling having AUC values

more than 0.90. Estimation of relative contributions of the environmental variables to the current model reveals a strong influence of bio 3, bio 17 and total carbon in both the depth. However, for SSP2-4.5 scenario projected for 2060, bio 9 and bio 18 have highest contribution to the model, whereas for SSP5-8.5 scenario, the bio 4 and and bio 14 layers have maximum contributions.

The ensemble model for the SSP5-8.5 scenario under CMCC model revealed that only 2.88% of the total area of NE states will be left as very high suitable area for the species, which is 12.86% under the current climate, while 3.01% has high suitability under optimistic climate scenario will be left till 2060 (Table 1; Fig. 3).

Table 1. Model evaluation statistics in current and future climate scenario.

Models	AUC	Sensitivity	Specificity	Kappa
Current	0.959	0.965	0.688	0.446
SSP2-4.5	0.970	0.955	0.703	0.428
SSP5-8.5	0.954	0.955	0.683	0.414

Table 2. Model evaluation statistics in current and future climate scenario.

Suitability Threshold	Percentage Area Covered		
	Current	SSP2-4.5	SSP5-8.5
High suitability	12.86	3.01	2.88
Moderate suitability	13.54	5.50	4.82
Low suitability	25.99	10.67	11.60
No suitability	47.62	80.82	80.70

Discussion

The present study highlighted the urgent need for the species conservation in their natural habitat. Modeling current habitats and forecasting the future species distribution range is an important step toward the species sustainability in their natural habitats (Kumari 2022). The present study is the first effort to map the current habitats (Fig. 4) and predict the sensitive variables on habitat suitability of *S. punduana*. Species distribution modelling is a useful tool to delineate conservation areas for threatened species (Roy 2022). Nevertheless, models generated using different programs often differ from each other causing inconveniences in coming to a definite conclusion (Ray et al. 2018). Such differences are evident from several studies, which despite using the same environmental predictors, yielded different results (Mipun et al. 2019). The current study also generated similar results, where we modeled the

distribution of potential habitat of *S. punduana* using ensemble model for both current and future climate (Fig. 5, Table 2). As plant species have wide range of factors for their survival, so considering maximum factors available in any respective habitat distribution model is essential. Such study of consensus areas using different models could lead to a new dimension in finding better suitable habitats.

The estimation of relative contributions of environmental variables under different scenarios reveals notable shifts in the key factors influencing the potential distribution of *Saurauia punduana*. In the current scenario, isothermality (Bio3), precipitation of the driest quarter (Bio17), and total soil carbon at both 5 cm and 15 cm depths emerged as the most influential predictors. These variables likely reflect the species' sensitivity to temperature stability and moisture availability during critical dry periods, along with its dependence on specific soil properties. However, under the SSP2-4.5 scenario projected for 2060, the most influential variables shift to mean temperature of the driest quarter (Bio9) and precipitation of the warmest quarter (Bio18). This indicates that rising temperatures and seasonal precipitation changes may become more critical in defining suitable habitats. In contrast, the SSP5-8.5 scenario-representing a more extreme climate pathway-shows a greater influence of temperature seasonality (Bio4) and precipitation of the driest month (Bio14), suggesting that the species' future distribution may be increasingly driven by climatic extremes and fluctuations. These changes underscore the vulnerability of *Saurauia punduana* to climate variability and highlight the need to consider scenario-specific climatic drivers in future conservation planning.

In the present study, the current species distribution model reveals that isothermality (bio3), precipitation in the driest quarter and soil carbon played a crucial role in discriminated the suitable and unsuitable habitats of *S. punduana* in its native range. Also, the population count of the *S. punduana* in the EKAWLS is low, meager number of populations was observed depicting low density of the species might be influence by precipitation in the winter months. The field surveys in EKAWLS revealed that the suitable natural habitats of the plant species concurred with the distribution of moist semi-evergreen forests at an elevation of 590–710 m asl having the slope range from 29–57 degrees and under the soil series 2 from soil series of Assam. The actual, as well as predicted habitats of *S. punduana*, have a cover of moist semi-evergreen forest type with mixed to open canopy opening characterized by the soil of loamy texture and a moderately drained slope. The dominant soil type in the area is dystric nitosol with humid acrisol as the associated soils and inclusions. The dominant tree species associated with *S. Punduana* comprise of *Baccaurea ramiflora* Lour., *Bridelia retusa* (L) Spreng., *Bauhinia variegata* L., *Careya arborea* Roxb., *Dillenia indica* L., *Magnolia hodgsonii* (Hk. f. & Thomson) H. Keng and *Wrightia coccinea* (Roxb. Ex Hornem.) Sims. The study established that habitat distribution modeling could be an effective tool in predicting the potential habitats of threatened species which can certainly improving their conservation status (Adhikari et al. 2012; Baruah et al. 2019). Results of the study suggest a strong relationship between potential habitat distributions and factors determining their distribution. Such consensus data generated by different machine learning tools along with various field expert data can potentially guide in conserving such threatened species to a greater extent.

During the study, it was observed that various types of anthropogenic threats are being faced within the studied area. Among them, overgrazing due to livestock, overexploitation of plants, introduction of invasive alien species was found to be more prevalent in the areas. Additionally, considering the recent decade challenges posed by widespread deforestation and habitat destruction (Ronghang et al. 2012; Mipun et al. 2019), it is urgent to develop some strategies to conserve those threatened plant species before they are lost forever. Moreover, economic interests should not prefer over environmental concerns and re-evaluation of the existing policies on the environment and economy is necessary as they struggle to achieve sustainable development goals.

Conclusion

The present study demonstrated that species distribution modelling using ensemble models could be of great help in predicting the potential habitats of threatened species. Moreover, consensus areas identified through spatial overlays of multiple models may help in obtaining optimized solutions and making better decisions in finding the most highly suitable common point areas for rehabilitating the species population and improving its conservation status. Many other potential species distribution models could also use such common consensus areas in finding the most suitable areas. Such engendered results based on machine learning would be quite useful for conserving threatened species and overall biological diversity.

This study shows that ensemble species distribution modelling is a powerful tool for predicting potential habitats of threatened species. Identifying consensus areas through multiple model overlays can help make better decisions for species recovery by highlighting the most suitable locations for conservation efforts. These areas can also guide future modelling efforts for other species. For *Saurauia punduana*, effective conservation should combine both in-situ and ex-situ approaches. Protecting habitats in highly suitable zones, restoring degraded areas, and considering the species' specific microhabitat needs in forest management plans are essential steps. Additionally, ex-situ measures such as seed banking, cultivation in botanical gardens, and carefully planned reintroductions can support population recovery. Using model outputs to guide regional conservation plans and policies will be vital for ensuring the species' long-term survival in the face of climate change.

Declarations

Acknowledgement

We are thankful to Botanical Survey of India, Eastern Regional Circle for allowing us to consult the herbarium. Dr. Dipankar Borah for the detail photography. The help and cooperation received from the local people is also thankfully acknowledged.

Availability of data and materials

Not applicable.

Authors' contributions

PM, DN, BSM conceived the idea and designed the experiment. PM, DN, BD collected and compiled field data. Analysis, writing and editing was done by PM, JS. Modeling was done by KS. All the authors read and approved the manuscript.

Ethics and consent to participate

The plant material (*Saurauia punduana*) was collected from EKAWLS following all relevant national and local guidelines and followed the provisions of the Biological Diversity Act, 2002. Necessary permissions were obtained from concerned Government authorities of Assam vide Ref. No. PCCF/KA/Wildlife/2015-16/886-89 dt. 15/09/2015. The plant material was collected from wild populations with minimal disturbance considering its CR status. Voucher specimens were prepared following standard herbarium techniques (Jain & Rao, 1977) and deposited in the North East Hill University Herbarium under Voucher No. NEHU-12948 .

Consent for publication

Not applicable

Competing interests

The authors declare that they have no competing interests.

Funding declaration

The authors declare that they have not received any funding for this work.

NOTES ON CONTRIBUTOR

Puranjoy Mipun is currently working as an Assistant Professor in the Department of Botany, Bhattadev University, Assam, and India. He has interest in Ecology and conservations aspects.

Kuladip Sarma is currently working as an Assistant Professor in the Department of Zoology, Gauhati University, Assam, India. He has a vast knowledge in modeling and working different conservation issues with modeling.

Jintu Sarma is as an Assistant Professor in the Department of Botany, Guwahati College, Guwahati, India. He has a vast experience in Plant taxonomy and biodiversity conservation alongwith ethnobotany of tribal community of Assam and North East India. He has lots of works related to flora of Assam and neighbouring states.

Deiji Narah is currently working as an Assistant Professor in the Department of Botany, Joya Gogoi College, Khumtai, Assam, India and she is working in the field of plant diversity and conservation.

Baby Doley is currently working as an Assistant Professor in the **Department** of Botany, DDR College, Chabua Assam, India.

Bijay Singh Mipun is currently serving as a Professor in the Department of Geography, Assam Royal Global University, Guwahati, India. He has a vast knowledge in land use patterns and ecology of plants of NE India and working since last three decades.

References

1. Adhikari D, Barik S, Upadhaya K (2012) Habitat distribution modelling for reintroduction of *Ilex khasiana* Purk. a critically endangered tree species of northeastern India. *Ecol Eng* 40:37–43. <https://doi.org/10.1016/j.ecoleng.2011.12.004>
2. Adhikari D, Mir AH, Upadhaya K et al (2018) Abundance and habitat-suitability relationship deteriorate in fragmented forest landscapes: a case of *Adinandra griffithii* Dyer, a threatened endemic tree from Meghalaya in northeast India. *Ecol Process* 7(1):1–9. <https://doi.org/10.1186/s13717-018-0114-z>
3. Antonelli, A., Smith, R. J., Fry, C., Simmonds, M. S. J., Kersey, P. J., Pritchard, H. W., et al. (2020). State of the World's Plants and Fungi. Royal Botanic Gardens (Kew); Sfumato Foundation.
4. Araujo MB, Williams PH, Fuller RJ (2002) Dynamics of extinction and the selection of nature reserves. *Proc R Soc Lond B Biol Sci* 269:1971–1980. <https://doi.org/10.1098/rspb.2002.2121>
5. Austin MP (2002) Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. *Ecol Model* 57: 101–118. <https://doi.org/10.1016/S0304-3800%2802%2900205-3>
6. Baruah PS, Deka K, Lahkar L, Sarma B, Borthakur SK, Tanti B (2019) Habitat distribution modelling and reinforcement of *Elaeocarpus serratus* L-a threatened tree species of Assam, India for improvement of its conservation status. *Acta Ecol Sin* 39(1):42–49. <https://doi.org/10.1016/J.CHNAES.2018.06.002>
7. Bhuyan, A., Bawri, A., Saikia, B. P., Baidya, S., Hazarika, S., Thakur, B., et al. (2025). Predicting habitat suitability of *Illicium griffithii* under climate change scenarios using an ensemble modeling approach. *Scientific Reports*, 15(1), 9691. <https://doi.org/10.1038/s41598-025-92815-x>
8. Bhuyan, A., Hazarika, S., Baidya, S., Sarma, K., Thakur, B., Prakash, A., & Devi, A. (2025). Assessing current and future potential habitat of *Vatica lanceaefolia* (Roxb.) Blume, a critically endangered tree species of Northeastern India. *Theoretical and Applied Climatology*, 156(2), 1–13. <https://doi.org/10.1007/s00704-025-05369-3>
9. Borthakur SK, Baruah PS, Deka K, Das P, Sarma B, Adhikari D, Tanti B (2018) Habitat distribution modelling for improving conservation status of *Brucea mollis* Wall. ex Kurz.-An endangered potential medicinal plant of Northeast India. *J Nat Conserv* 43:104–110. <https://doi.org/10.1016/J.JNC.2018.02.010>

10. Brummitt NA, Bachman S et al (2010) Plants under pressure-a global assessment: the first report of the IUCN sampled red list index for plants. Royal Botanic Gardens, Kew
11. Cabeza M, Araujo MB, Wilson RJ, Thomas CD, Cowley MJR, Moilanen A (2004) Combining probabilities of occurrence with spatial reserve design. J Appl Ecol 41:252–262.
<https://doi.org/10.1111/j.0021-8901.2004.00905.x>
12. Champion HG, Seth SK (1968) A Revised Survey of Forest Types of India, Govt of India Press, New Delhi, p 404
13. Chanda S, Mukherjee A (2012) Non-timber forest products as documented from the Paharia tribe of Ayodhya Hills in Purulia district of West Bengal (India). Acta Botanica Hungarica 54(3-4):269–275.
<https://doi.org/10.1556/abot.54.2012.3-4.6>
14. Corbin AE (2015) Towards estimating leaf water content through hyperspectral data. University of Twente student theses. <https://purl.utwente.nl/essays/84031>
15. Corlett RT (2016) Plant diversity in a changing world: status, trends, and conservation needs. Plant Divers 38(1):10–16. <https://doi.org/10.1016/j.pld.2016.01.001>
16. Deb CR, Gangmei PK (2017) Callus Mediated Indirect Somatic Embryogenesis and Plant Regeneration of *Saurauia punduana* Wallich (Actinidiaceae) from In Vitro Cotyledonary Leaves. Current Biotechnology 6(1):69–76. <https://doi.org/10.2174/2211550105666160112001422>
17. Dobriyal MJ, Dobriyal R (2014) Non wood forest produce-an option for ethnic food and nutritional security in India. Int J of Usuf Mngt 15:17–37
18. Dobriyal MJR, Dobriyal R (2014) Non wood forests produce an option for ethnic food and nutritional security in India. Intn J Usuf Mngt 15(1):17–37
19. Evans MR (2012) Modelling ecological systems in a changing world. Philos Trans R Soc Lond B Biol Sci 367(1586):181–190. <https://doi.org/10.1098/rstb.2011.0172>
20. Ferrier S (2002) Mapping spatial pattern in biodiversity for regional conservation planning: where to from here? Syst Biol 51(2):331–363. <https://doi.org/10.1080/10635150252899806>
21. Goswami J, Tajo L, Sarma KK (2010) Bamboo resources mapping using satellite technology. Curr Sci 99(5):650–653
22. Guisan A, Thuiller W (2005) Predicting species distribution: offering more than simple habitat models. Ecol Lett 8:993–1009. <https://doi.org/10.1111/j.1461-0248.2005.00792.x>
23. Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz SJ, Loveland TR, Kommareddy A, Egorov A, Chini L, Justice CO, Townshend JRG (2013) High-resolution global maps of 21st century forest cover change. Science 342:850–853.
<https://doi.org/10.1126/science.1244693>
24. Haridasan K, Rao RR (1987) Forest Flora of Meghalaya, vol 2. Bishen Singh Mahendra pal Singh, Dehradun, p 937
25. Hernandez PA, Graham CH, Master LL, Albert DL (2006) The effect of sample size and species characteristics on performance of different species distribution modeling methods. Ecography

- 29(5):773–785. <http://dx.doi.org/10.1111/j.0906-7590.2006.04700.x>
26. Hunt ER, Qu JJ, Hao X, Wang L (2009) Remote Sensing of Canopy Water Content: Scaling from Leaf Data to MODIS. In Proceedings of SPIE - The International Society for Optical Engineering, p 7454
 27. Huston MA (2002) Introductory essay: critical issues for improving predictions. In: Predicting Species Occurrences: Issues of Accuracy and Scale (eds Scott JM, Heglund PJ, Morrison ML, Haufler JB, Raphael MG, Wall WA, Samson FB). Island Press, Covelo, CA, pp 7–21
 28. IUCN (2020) Red List of Threatened Species. A Global Species Assessment. IUCN, Gland, Switzerland and Cambridge, UK
 29. Johnson NF (2007) Biodiversity informatics. *Annu Rev Entomol* 52: 421–438
 30. Johnson SE, Delmore KE, Brown KA, Wyman TM, Louis EE (2016) Niche divergence in a brown lemur (*Eulemur spp.*) hybrid zone: Using ecological niche models to test models of stability. *Int J Primatol* 37:69–88. <https://doi.org/10.1007/s10764-015-9872-y>
 31. Jones KR, Venter O, Fuller RA, Allan JR, Maxwell SL, Negret PJ, Watson JEM (2018) One-third of global protected land is under intense human pressure. *Science* 360(6390):788–791. <https://doi.org/10.1126/science.aap9565>
 32. Kamilar JM, Tecot SR (2016) Anthropogenic and climatic effects on the distribution of *Eulemur* species: an ecological niche modeling approach. *Int J Primatol* 37:47–68. <https://doi.org/10.1007/s10764-015-9875-8>
 33. Kanjilal VN, Kanjilal PC, Das A, De RN, Bor NL (1940) Flora of Assam, vol 5. Government Press, Shillong
 34. Kelling S, Hochachka WM, Fink D, Riedewald M, Caruana R, Ballard G, Hooker G (2009) Data-intensive science: a new paradigm for biodiversity studies. *Biosci* 59(7):613–620. <http://dx.doi.org/10.1525/bio.2009.59.7.12>
 35. Körner C (2007) The use of ‘altitude’ in ecological research. *Trends in ecology & evolution* 22(11):569–574. <https://doi.org/10.1016/j.tree.2007.09.006>
 36. Kumari P, Wani IA, Khan S, Verma S, Mushtaq S, Gulnaz A, Paray BA (2022) Modeling of *Valeriana wallichii*: Habitat Suitability and Niche Dynamics in the Himalayan Region under Anticipated Climate Change. *Biology* 11(04):498. <http://dx.doi.org/10.3390/biology11040498>
 37. Kundu S, Mukherjee T et al (2023) Matrilineal phylogeny and habitat suitability of the endangered spotted pond turtle (*Geoclemys hamiltonii*; Testudines: Geoemydidae): a two-dimensional approach to forecasting future conservation consequences. *PeerJ* 11(suppl_2):e15975. <https://doi.org/10.7717/peerj.15975>
 38. Lan H, Wang D, He S, Fang Y, Chen W, Zhao P, Qi Y (2020) Experimental study on the effects of tree planting on slope stability. *Landslides* 17:1021–1035. <https://doi.org/10.1007/s10346-020-01348-z>
 39. Menges ES (1991) The application of minimum viable population theory to plants. In: (ed) Falk DA and Holsinger KE Genetics and conservation of rare plants. New York, Oxford University Press, pp 45–61

40. Michener WK, Jones MB (2012) Ecoinformatics: supporting ecology as a data-intensive science. *Trends Ecol Evol* 27(2):85–93. <https://doi.org/10.1016/j.tree.2011.11.016>
41. Mipun P, Adhikari D, Bora A, Bhat NA, Kumar Y (2019) Species distribution modelling of *Brucea mollis* wall. ex kurz in Northeast India for its conservation. *Plant Arch* 19(2):3191–3196
42. Mipun P, Bhat NA, Borah D, Kumar Y (2019) Non-timber forest products and their contribution to healthcare and livelihood security among the Karbi tribe in Northeast India. *Ecological Processes* 8:1-21. <http://dx.doi.org/10.1186/s13717-019-0194-4>
43. Mir AH, Sarma K, Upadhaya K (2022) Assessing the effectiveness of community managed forests for plant diversity conservation in Meghalaya, Northeast India. *Plant Diversity* 44(3):243–254. <https://doi.org/10.1016/j.pld.2021.11.010>.
44. O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., Van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Clim. Change* 122, 387–400. <https://doi.org/10.1007/s10584-013-0905-2>
45. Pasaribu G, Budianto E, Cahyana H, Saepudin, E (2020) A Review on Genus *Saurauia*: Chemical Compounds and their Biological Activity. *Pharmacogn J* 12(3):657–666. <http://dx.doi.org/10.5530/pj.2020.12.97>
46. Phillips SJ, Anderson RP, Schapire RE (2006) Maximum entropy modeling of species geographic distributions. *Ecol Model* 190(3):231–259. <https://doi.org/10.1016/j.ecolmodel.2005.03.026>
47. Potić I, Bugarski M, Matić-Varenica J (2017) Soil moisture determination using remote sensing data for the property protection and increase of agriculture production. In 2017 Annual World Bank conference on land and poverty, Washington DC
48. POWO (2025) Plants of the World Online. Facilitated by the Royal Botanic Gardens, Kew. Published on the Internet; <https://powo.science.kew.org/>. Accessed 26 December 2024
49. Rai PK, Singh JS (2020) Invasive alien plant species: Their impact on environment, ecosystem services and human health. *Ecol Indic* 111:106020
50. Ray D, Behera MD, Jacob J (2018) Evaluating Ecological Niche Models: A Comparison Between Maxent and GARP for Predicting Distribution of *Hevea brasiliensis* in India. *Proc Natl Acad Sci, India, Sect B Biol Sci* 88:1337–1343. <https://doi.org/10.1007/s40011-017-0869-5>
51. Ronghang R, Teron R, Tamuli AK, Rajkhowa CR (2012) Tribal societies and deforestation in Karbi Anglong District of Assam (India). *The Ecoscan* 1:231–236
52. Roy S, Suman A, Ray S, Saikia SK (2022) Use of species distribution models to study habitat suitability for sustainable management and conservation in the Indian subcontinent: A decade's retrospective. *Frontiers in Sustainable Resource Management* 1:1031646. <https://doi.org/10.3389/fsrma.2022.1031646>
53. Riahi K., Van Vuuren, DP, Kriegler E, Edmonds J, O'Neill BC, Fujimori S, Bauer N, Calvin K, Dellink R, Fricko O (2017) The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Glob. Environ. Chang.* 42, 153–168. <https://doi.org/10.1016/j.gloenvcha.2016.05.009>

54. Sarma, K., Roy, S. J., Kalita, B., Regon, P., Bawri, A., Sahariah, D., et al. (2024). Impact of climate change on potential distribution and altitudinal shift of critically endangered *Amentotaxus assamica* DK Ferguson in Arunachal Pradesh Himalaya, India. *Theoretical and Applied Climatology*, 155(1), 261–271. <https://doi.org/10.1007/s00704-023-04628-5>
55. Schmitt, S., Pouteau, R., Justeau, D., De Boissieu, F., & Birnbaum, P. (2017). ssdm: An r package to predict distribution of species richness and composition based on stacked species distribution models. *Methods in Ecology and Evolution*, 8(12), 1795–1803. <https://doi.org/10.1111/2041-210X.12841>
56. Shackleton RT, Shackleton CM, Kull CA (2019) The role of invasive alien species in shaping local livelihoods and human well-being: a review. *J Environ Manage* 229:145–157
57. Sharma RC, Grewal JS, Sharma AK, Sharma HC (1980) Relative efficiency of calcium ammonium nitrate, dimethyl urea, urea and urea coated with neem cake for potato. *Indian J Agric Sci* 50:152–157
58. Thuiller W, Lavorel S, Araújo MB, Sykes MT, Prentice IC (2005) Climate change threats to plant diversity in Europe. *Proc Natl Acad Sci USA* 102(23):8245–8250. <https://doi.org/https://doi.org/10.1073/pnas.0409902102>
59. Thuiller W, Münkemüller T (2010) Habitat suitability modeling. In: Moeller AP, Fielder W, Berthold P (ed) *Effects of climate change on birds*, Oxford University Press, pp 77-85
60. Tiwary, R., Singh, P. P., Adhikari, D., Behera, M. D., & Barik, S. K. (2024). Vulnerability assessment of *Taxus wallichiana* in the Indian Himalayan Region to future climate change using species niche models and global climate models under future climate scenarios. *Biodiversity and Conservation*. <https://doi.org/10.1007/s10531-024-02859-0>
61. Tsoar A, Allouche O, Steinitz O, Rotem D, Kadmon R (2007) A comparative evaluation of presence-only methods for modelling species distribution. *Diversity and Distributions* 13(4): 397–405. <https://doi.org/10.1111/j.1472-4642.2007.00346.x>
62. Veihmayer FJ, Hendrickson AH (1927) Soil moisture conditions in relation to plant growth. *Plant Physiology* 2(1):71–82. <https://doi.org/10.1104/pp.2.1.71>
63. Wiens JA (2002) Predicting species occurrences: progress, problems, and prospects. In: Scott JM, Heglund PJ, Morrison ML, Haufler JB, Raphael MG, Wall WA, Samson FB (ed) *Predicting Species Occurrences: Issues of Accuracy and Scale*. Island Press, Covelo, CA, pp 739-749
64. Williams PH, Araujo MB (2000) Using probability of persistence to identify important areas for biodiversity conservation. *Proc R Soc Lond B Biol Sci* 267:1959–1966. <http://dx.doi.org/10.1098/rspb.2000.1236>
65. WWF India (2002). <http://www.wwfindia.org>. Accessed 26 December 2024
66. Xue J, Su B (2017) Significant remote sensing vegetation indices: a review of developments and applications. *Journal of Sensors* 2017:1–17. <https://doi.org/10.1155/2017/1353691>
67. Yilmaz MT, Hunt ER, Jackson TJ (2007) Remote sensing of vegetation water content from equivalent water thickness using satellite imagery. *Science Direct* 112:2514–2522

68. Zimmermann NE, Edward TC, Graham CH, Pearman PB, Svenning JC (2010) New trends in species distribution modelling. *Ecography* 33:985–989

Figures

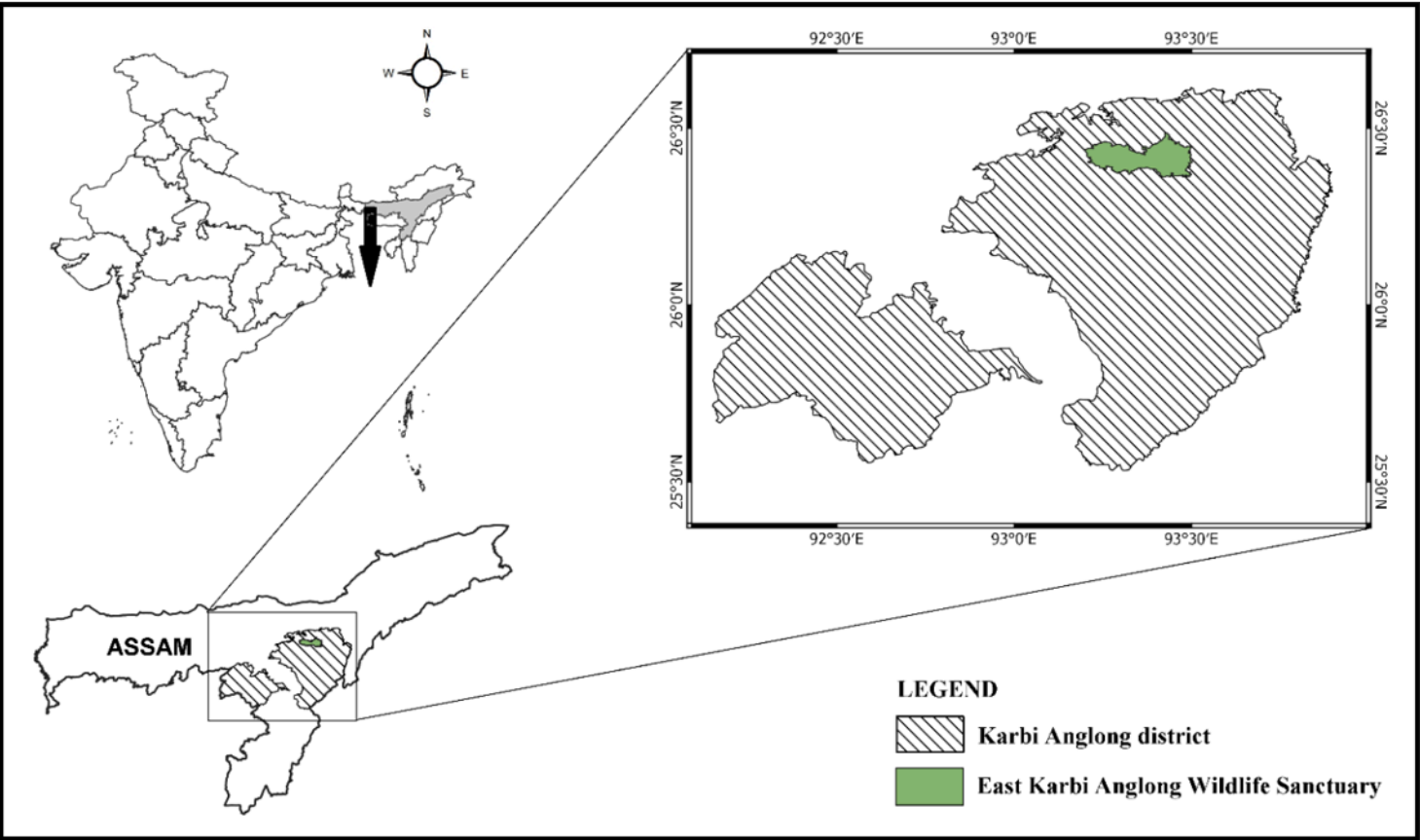


Figure 1

Showing the Study area East Karbi Anglong Wildlife Sanctuary (EKAWLS)

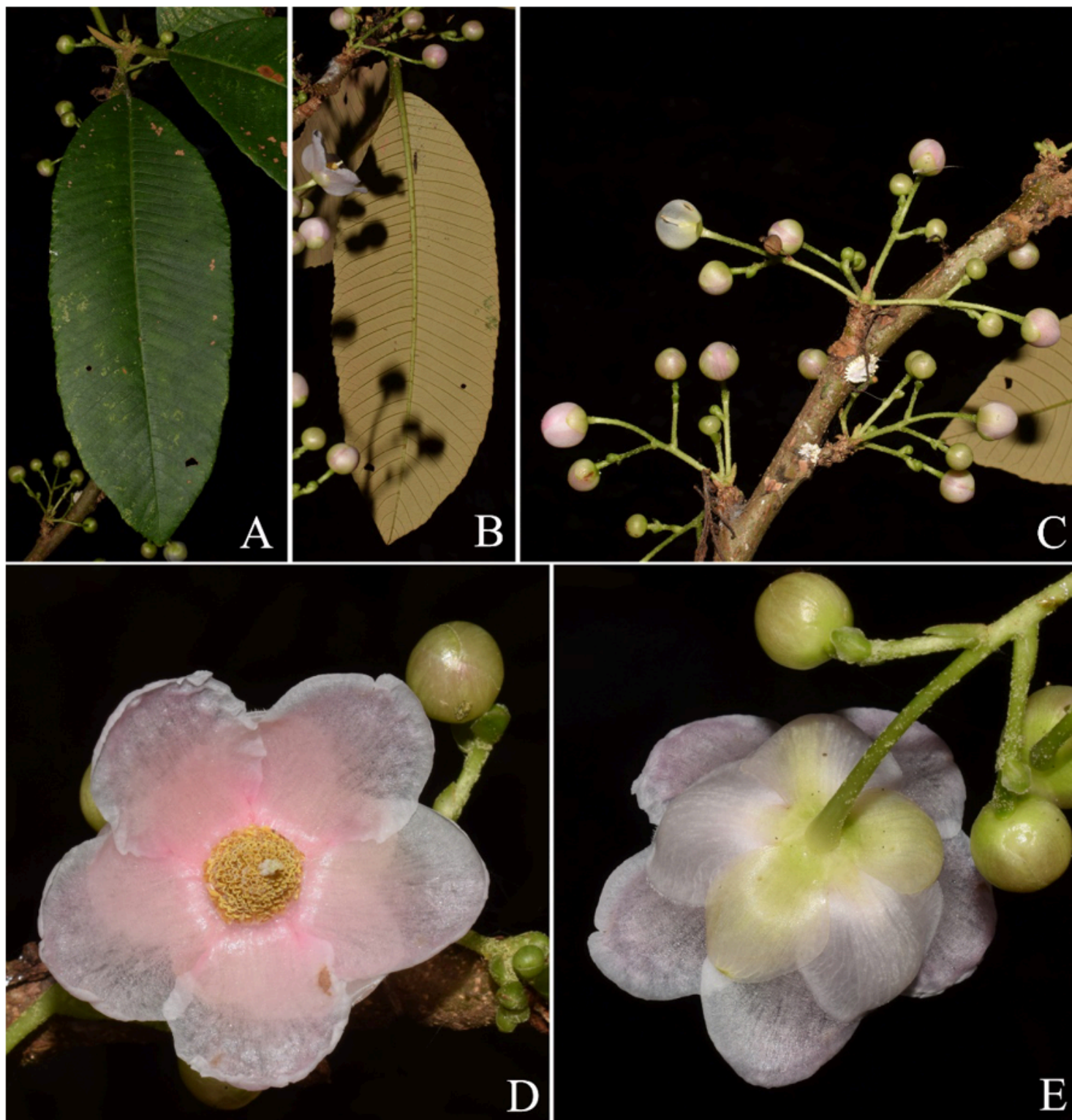


Figure 2

A. adaxial surface of a leaf, B. abaxial surface of leaf: showing brown scurfy puberulent indumentum, C. Twig, showing glabrescent branches, D. Flower front view, showing the anthers and style, E. Flower back view, showing glabrous calyx



Figure 3

Figure A & B Habitat photo of *Saurauia punduana* in EKAWS.

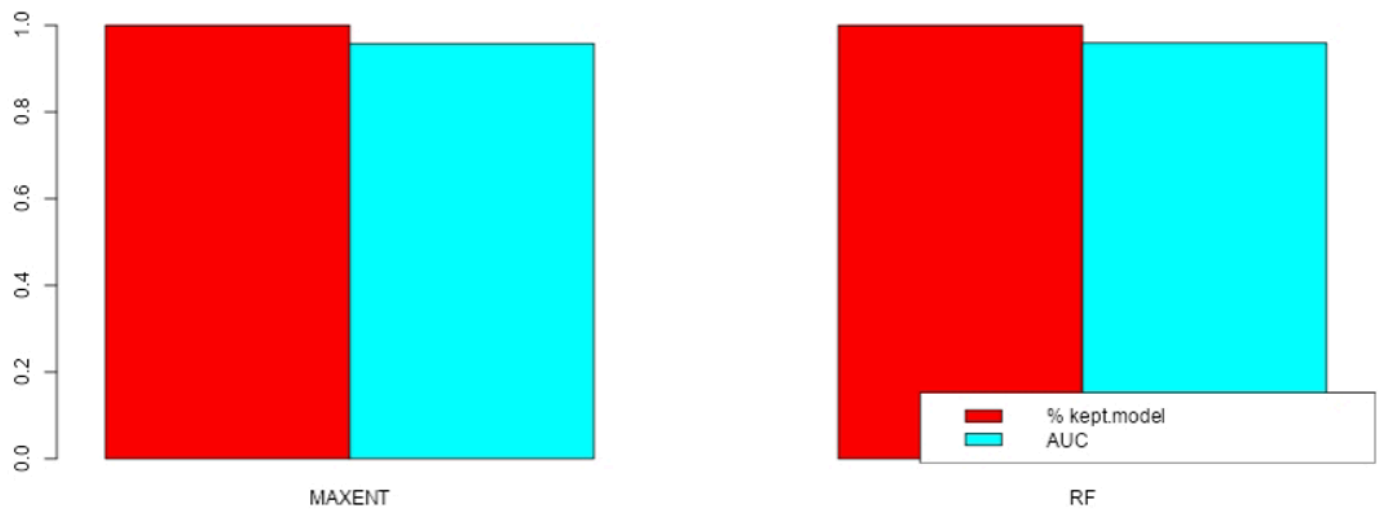


Figure 4

Figure 3. Model AUC for both Maxent and Random Forest

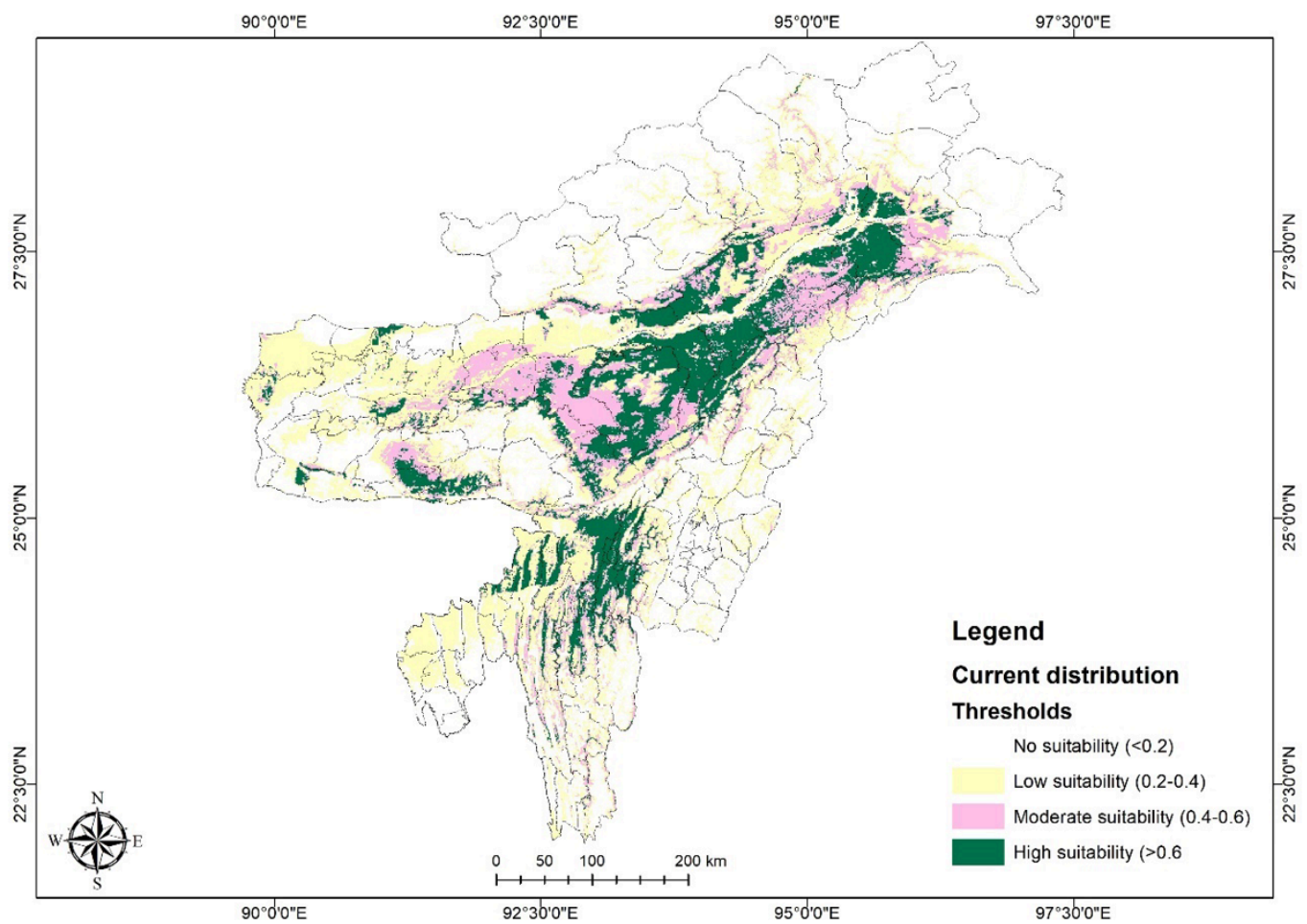


Figure 5

Figure. 4. Habitat suitability map of *S. punduanain* the current climatic scenario in Northeast India

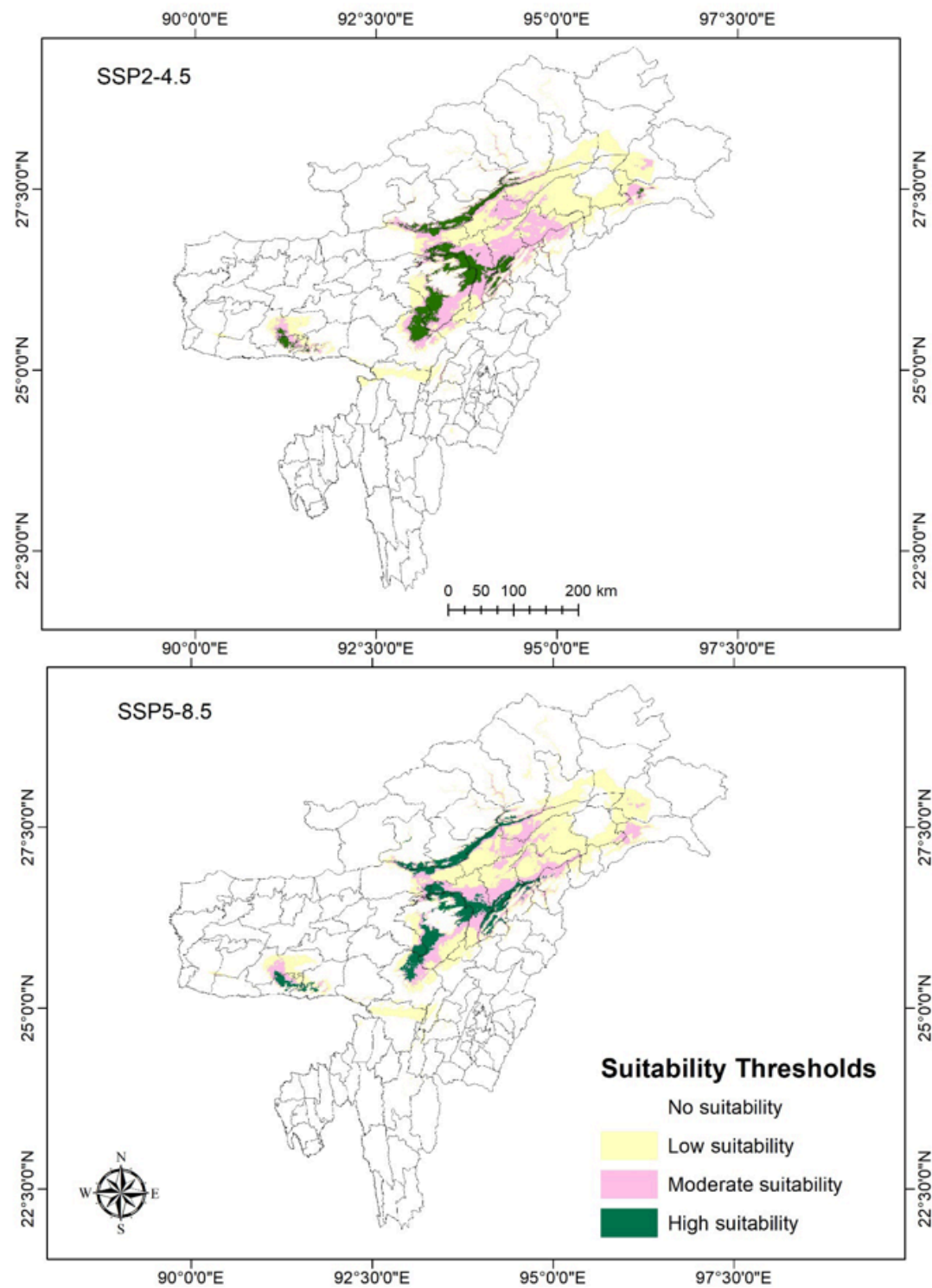


Figure 6

Figure 5. Habitat suitability map of *S. punduanain* two different climatic scenarios (SSP2-4.5 and SSP5-8.5) in Northeast India