

Prioritizing Suitable Habitat for the Cultivation and Conservation of the High-Value Medicinal Tree *Rhus chinensis* in Sikkim, Eastern Himalaya, India

ADITYA PRADHAN¹, BIJOY CHHETRI² AND ARUN CHETTRI^{3*}

¹Department of Botany, ²Department of Zoology, School of Basic Sciences, SRM University Sikkim, 5th mile, Tadong, 737102, Gangtok, Sikkim, India

³Department of Botany, School of Life Science, Sikkim University, 6th mile, Tadong, 737102, Gangtok, Sikkim

E-mail: apradhan512@gmail.com, chhetribijoy@yahoo.in, achettri01@cus.ac.in

***Corresponding author**

ABSTRACT

Wild edible fruits (WEFs) are often underutilized and overlooked due to limited knowledge of their traditional medicinal uses and nutritional value. Among many WEFs, *Rhus chinensis* has a long history of use in ethnomedicinal practices among indigenous peoples of Northeast India. The present study highlights the use of ecological modelling tools to identify suitable habitats for *R. chinensis* in the Sikkim Himalaya. Among the input variables, the Normalized Difference Vegetation Index (NDVI) and soil water stress for January together accounted for 49.6% of the model output, underscoring the importance of fruiting phenology in species distribution. Of the total predicted area, most falls within the very low suitability class (74.2%), followed by low (9.37%), moderate (7.55%), high (5.51%), and very high (3.34%). These results indicate that very little area is suitable for *R. chinensis* in Sikkim. The species is primarily found at lower elevations in the Sikkim Himalaya, where extensive development activities, including road widening, threaten its natural habitat. Additionally, most of the highly suitable predicted regions fall outside protected areas, posing an additional risk of future population decline. Therefore, to safeguard the existing population of *R. chinensis*, the identified suitable protected areas should be prioritized for in situ conservation, thereby preserving the traditional knowledge associated with the species.

Key words: Distribution, ENM, Protected area, Population assessment, *Rhus*, WEFs

INTRODUCTION

India's rich biotic resources cover approximately 2.24% of the global area and 8% of the world's biodiversity (Chitale et al. 2014). Since the Indian Himalayan region is home to 1748 medicinal plant species, it is a key area for cultivating medicinal plants (Joshi et al. 2016). Sikkim, the Himalayan state, lies between 27° 46' and 28° 7' 48' N latitude and 88° 0' 5" and 88° 55' 25" E longitude, and is part of the Eastern Himalayas. The state is often called the 'Cradle of Flowering Plants' because of its rich repository of medicinal and aromatic plant resources (Rai et al. 2000). The hill state of India, located in the Eastern Himalaya, has highly diverse plant life, with more than 200 species traditionally used as wild edibles (Sundriyal and Rai 1994, Sharma 2016). *Rhus chinensis* Mill. (Anacardiaceae) is one such tree with high medicinal value that has been used by traditional healers across Asia (Djakpo and Yao 2010). The species is currently classified as of least concern by the IUCN. However, due to its high medicinal value and ongoing use within indigenous medical systems (Sharma et al. 2019), it could face significant threats in the future. Thus, conserving the habitat of *R. chinensis* is essential for protecting the species and

the associated traditional knowledge. Conservation efforts for species or biodiversity generally focus on protected areas of various categories. Nonetheless, more than 90% of Earth's terrestrial surface is not covered by any protected area. In this context, traditional agro-ecosystems play a crucial role in conserving biodiversity outside designated protected zones (Halladay and Gilmour 1995). One approach for protecting and conserving species involves identifying habitat suitability using Ecological Niche Modelling (ENM). ENM is a machine learning tool widely used to predict the distribution of suitable habitats based on species presence data (Phillips and Dudik 2008). Although several tools are available for predicting species distribution, MaxEnt has become particularly popular since its introduction (Renner and Warton 2013). While the traditional knowledge, economic value, and medicinal importance of *R. chinensis* are well recognized, there is a lack of data about its distribution and population status in Sikkim. Therefore, this study was conducted with the objectives: (a) to assess the current population status of *R. chinensis* and (b) to identify suitable habitats for its cultivation and conservation in the Sikkim Himalaya.

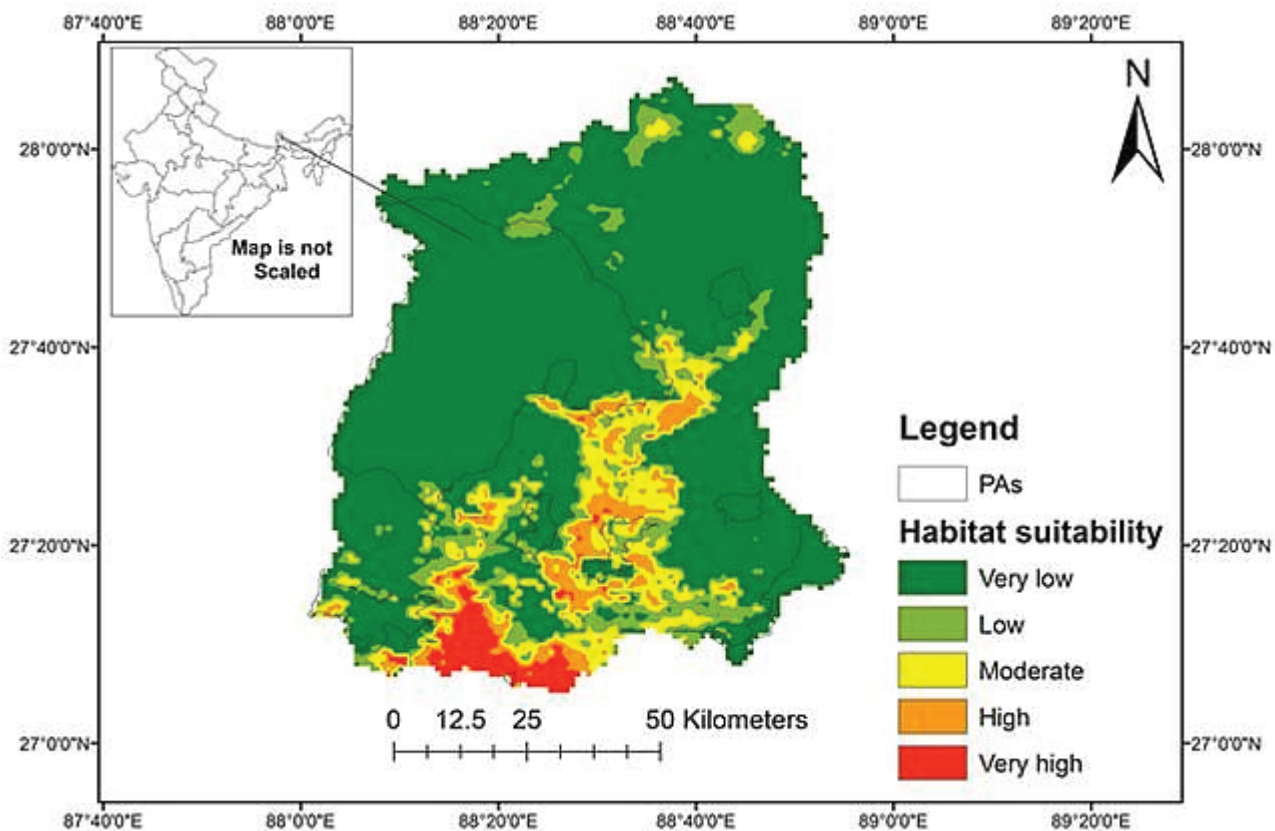


Figure 1. Predicted distribution map of *R. chinensis* in Sikkim, India

METHODS

Studied species and locality data

Rhus chinensis is a highly valued yet underutilized medicinal plant (Chhetri et al. 2019, Bhusal et al. 2024). In Sikkim, local traditional healers frequently use the species to treat various ailments. To gather occurrence data, including geographic coordinates, extensive field surveys were carried out across all districts of Sikkim. Consequently, 21 collection sites were identified, with locations recorded using a Garmin GPS device accurate to 3-10 m.

Ecological niche modelling

MaxEnt ver. 3.3. (Phillips et al. 2006) was used to model the species' distribution in the present study. MaxEnt is a machine-learning technique that estimates the target species' maximum entropy based on fixed restrictions (constraints) and provides reliable results with small sample sizes (Pearson et al. 2007). The model was run with 20 replicates and a 10th-percentile training threshold. The remaining parameters were kept at their default settings.

Population assessment and protected area analysis

The total number of individuals of the target species and their occurrence sites were recorded using an opportunistic sampling method (Chettri et al.

2018, Isaac et al. 2020). A total of 18 populations were found at the different occurrence sites in the study areas. The effectiveness of the protected areas of the study areas was assessed by overlaying the predicted distribution maps of the target species onto the present protected areas (Pradhan and Chettri 2017). The network was downloaded from the World Database of Protected Areas (UNEP-WCMC 2012, <http://protectedplanet.net>). The analysis was performed using ArcGIS v.10.3.

Variables

The NDVI data were obtained from the Global Land Cover Facility (GLCF) (University of Maryland, USA), and potential evapotranspiration and soil water stress data were sourced from CGIAR (Trabucco and Zomer 2019).

Calibrating the model

The potential environmental variables were selected using ENM Tool 1.3 (Warren et al. 2010). This tool quantifies mutual relationships among variables and tests autocorrelation between each pair of environmental variables. Variables with the highest loading values (>0.9) in the ENM Tool 1.3 output were excluded from the final model. Out of 49 environmental predictors, 14 were selected based on their minimum loading values, and 14 were treated as independent and non-correlated predictors at a 95%

confidence level. The Jackknife validation method and the 10-percentile threshold rule were applied, along with a regularisation multiplier of 1.5 to avoid model overfitting. For model development, 80% of the occurrence data were used for training, and the remaining 20% for testing. The model was run with 20 replicate iterations to improve the robustness and reliability of the predictions. The final habitat suitability map was developed by averaging the outputs from all model replicates, thereby reducing the impact of random variation and boosting model stability (Chhetri et al. 2021).

Execution of MaxEnt

To quantify model accuracy, goodness of fit was assessed using the area under the receiver operating characteristic curve (AUC), which indicates perfect discrimination between true and false positives in the confusion matrix. The AUC ranges from 0.5 to 1, with higher values indicating better performance: values above 0.9 denote excellent predictive ability, 0.7 to 0.9 indicate good performance, and values near 0.5 suggest poor or uninformative predictions (Swets 1988). The final output was classified into five threshold habitat categories and ranged into percentages from 0–100%: very low class ($\leq 10\%$), low class (11–30%), moderate class (31–50%), high class (51–70%), and very high class ($\geq 70\%$) following Chhetri et al. (2021). The partial AUC matrix was also used to assess the model’s performance. The partial AUC was estimated using the Niche Toolbox available online (<http://shiny.conabio.gob.mx:3838/nichetoolb2/>).

RESULTS AND DISCUSSION

Potential distribution

The predicted suitable area predominantly falls into the very low suitability category, covering 5265.85 km² (74.2%). The combined high and very high suitability zones make up only 628.457 km², accounting for 8.85% of Sikkim’s total area (Table 1). Among protected regions, Fambong Lho Wildlife

Table 1. Area predicted to be suitable under different habitat classes

Habitat suitability class	Suitable area (km ²)	%
Very low	5265.85	74.2
Low	665.57	9.38
Moderate	536.094	7.56
High	391.20	5.52
Very high	237.257	3.34
Total	7096	100

Sanctuary shows the highest proportion of very high suitability (19.7%), followed by Kyongnosla Alpine Sanctuary (7.89%), Maenam Wildlife Sanctuary (6%), Barsey Rhododendron Sanctuary (4.9%), Shingba Rhododendron Sanctuary (2.04%), Khangchendzonga National Park (0.84%), and Kitam Bird Sanctuary (Table 2). The species remains at risk of extinction and faces increasing threats from extensive development activities such as road widening and railway construction. To safeguard the existing population, priority should be given to protecting suitable habitats through in situ conservation. Currently, Sikkim has only one lower-elevation protected area, the Kitam Bird Sanctuary, putting tropical plant species in these regions at greater risk of extinction. Prior studies have recommended expanding the protected area network by 896 km², including the addition of three new protected areas in Sikkim (Kumar and Pandit 2019).

Model performance

The model’s performance was evaluated using the AUC. The results of the evaluation, including full and partial ROC-AUC measures, are shown in Table 3. The distribution of AUC ratios was significantly higher than expected by chance, indicating good

Table 2. Area under different suitability classes in the protected areas of Sikkim

Habitat suitability class	FBW	KIT	KNP	KYO	MAE	PAG	SGB	BAS
Very High	19.70	0.00	0.84	7.89	6.00	0.74	2.04	4.90
High	18.18	0.00	0.58	0.00	6.00	0.74	0.00	6.29
Moderate	9.09	66.67	1.26	2.63	4.00	0.74	14.29	4.90
Low	22.73	0.00	2.20	26.32	8.00	0.74	16.33	9.09
Very low	30.30	33.33	95.12	63.16	76.00	97.04	67.35	74.83

Note: FBW - Fambong Lho Wildlife Sanctuary, BAS - Barsey Rhododendron Sanctuary, SGB - Shingba Rhododendron Sanctuary, PAG - Pangolakha Wildlife Sanctuary, MAE - Maenam Wildlife Sanctuary, KYO - Kyongnosla Alpine Sanctuary, KNP - Khangchendzonga National Park, KIT - Kitam Bird Sanctuary

Table 3. Results of SDM performance using full and partial ROC measures

ROC space	Omission proportion	Mean AUC model ($\pm$ SD)	Mean AUC ratio($\pm$ SD)
ROC full	0	0.93 ($\pm$ 0.09)	-
ROC partial	0.05	0.97 ($\pm$ 0.01)	1.95 ($\pm$ 0.02)

model consistency (Fig. 2).

Contributing variables

The NDVI and soil water stress data for January collectively contributed 49.6% to the model's output, emphasizing the role of fruiting phenology in species distribution (Fig. 3). NDVI was chosen because it is a vital environmental predictor that improves model accuracy by reflecting vegetation structure and seasonal changes (Sloyer et al. 2019). Additionally, many previous studies have used NDVI to characterize taxon distributions (Adhikari et al. 2018, Lepcha et al. 2019).

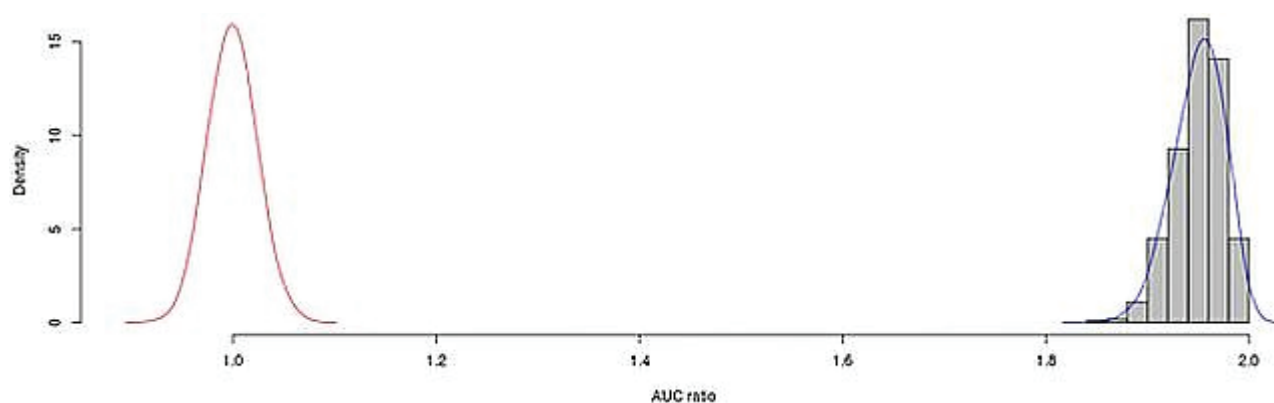


Figure 2. Partial AUC distribution for *R. chinensis* generated after 500 iterations for the bootstrap with a 0.05 proportion of omission and 50% random points. The blue curve on the right, along with shaded bars, represents the frequency distribution between AUC from model prediction and AUCrandom. The red curve on the left side represents the distribution of AUC ratios for random models.

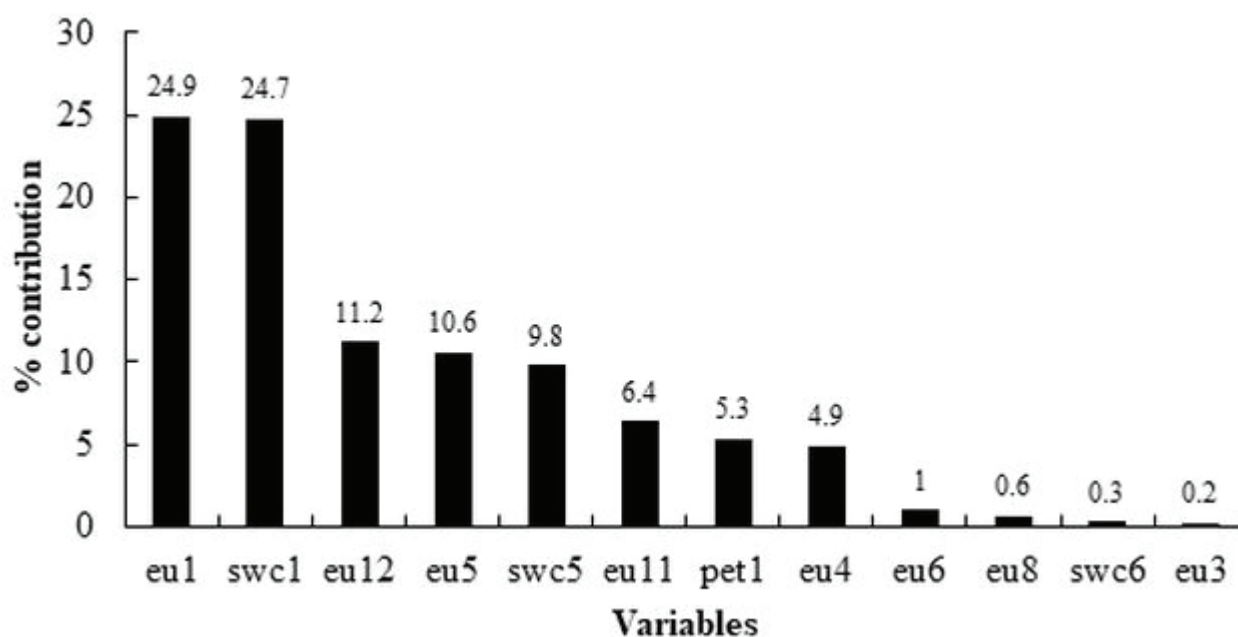


Figure 3. Percentage contribution of 13 variables to model output (Note: eu indicates NDVI; swc indicates Soil water stress and PET (which indicates evapotranspiration))

Population assessment

A total of 90 *R. chinensis* individuals were recorded in the predicted suitable habitat. The highest number was found in West Sikkim (49), followed

by 16 in each of the North and East districts, and 9 in the South district of Sikkim. Similarly, the very high and high suitability classes contained the most individuals (73), indicating greater species

Table 4. Population status of *R. chinensis* related to model probability values

Locality/District	Geographic coordinates	Current habitat	Habitat suitability class	Probability value (0-1)	No. of individuals
Lingay, East Sikkim	88.15761 E 27.14182 N	Human settlement, cultivated land	Very High	0.826	3
Daramdin, West Sikkim	88.17471 E 27.1424 N	Agroforestry	Very High	0.831	7
Daramdin, West Sikkim	88.17683 E 27.14251 N	Agroforestry	Very High	0.831	8
Zoom 1, West Sikkim	88.29111 E 27.16256 N	Agroforest, human settlement	Very High	0.949	7
Utaray1, West Sikkim	88.3008 E 27.1611 N	Agroforestry	Very High	0.909	2
Utaray, 2 West Sikkim	88.2991 E 27.15207 N	Agroforestry	Very High	0.943	2
Utaray 3, West Sikkim	88.30788 E 27.16158 N	Agroforestry	Very High	0.866	4
Utaray 4, West Sikkim	88.30926 E 27.16327 N	Agroforestry	Very High	0.866	5
Mangan, North Sikkim	88.52768 E 27.39831 N	Agroforestry	High	0.761	5
Dikchu, East Sikkim	88.50207 E 27.38212 N	Agroforest	High	0.736	7
Jorethang, South Sikkim	88.285 E 27.2706 N	Agroforest	High	0.677	7
Zoom West Sikkim	88.30887 E 27.22076 N	Agroforest, human settlement	High	0.694	6
Mangan, North Sikkim	88.52644 E 27.3981 N	Agro forest	High	0.669	6
Pakyong, East Sikkim	88.52699 E 27.24647 N	Human settlement, agroforestry	High	0.663	4
Chakung, West Sikkim	88.31281 E 27.21912 N	Agroforest, human settlement	Moderate	0.497	1
Soreng, West Sikkim	88.21826 E 27.15667 N	Agroforest, human settlement	Moderate	0.430	4
Chakung 1, West Sikkim	88.31913 E 27.21687 N	Agroforest, human settlement	Moderate	0.543	2
Dzongu, North Sikkim	88.50955 E 27.46367 N	Agroforest	Moderate	0.412	5
Pakyong, East Sikkim	88.59544 E 27.22834 N	Human settlement, agroforestry	Low	0.361	2
Yangang, South Sikkim	88.43339 E 27.31704 N	Agroforest	Low	0.232	2
Dentham West, Sikkim	88.22603 E 27.33535 N	Agroforest, human settlement	Very Low	0.154	1

Note: Habitat suitability thresholds: very low (0-0.2); low (0.2-0.4), medium (0.4-0.6), high (0.6-0.8), very high (0.8-1)

abundance than the medium (12), low (4), and very low (1) habitat suitability classes (Table 4). The species primarily occurs in the agroforestry systems of Sikkim, including forest areas and cultivated fields (Sharma et al. 2019). According to our field survey results and model outputs, the species also thrives in agroforestry environments and near human settlements (Table 3). With higher species richness in the western region, where it exists in farmed fields within agroforestry systems, suitable habitats for *R. chinensis* are primarily located at lower elevations of West and South Sikkim (Table 4).

CONCLUSIONS

The suitable habitats identified both within and outside protected areas must be prioritized for in situ conservation of the species. Considering the species' significant medicinal potential and its regular use by traditional healers, it is crucial to encourage local farmers to cultivate this valuable medicinal tree, especially within Sikkim's agroforestry systems. The identified suitable habitat can also serve as a site for cultivation, as such practices not only aid in conserving the species but also help preserve the plant's traditional knowledge. Therefore, it is important to recognize that this underutilized tree could serve as an alternative source of income for the local population, thereby supporting societal uplift. Overall, the modelling framework establishes a scientific foundation for identifying conservation priorities and addressing evidence-based decision-making in biodiversity conservation. The prioritized habitats identified in this study offer guidance to policymakers, forest managers, and conservation practitioners on developing targeted management interventions, optimizing resource allocation, and formulating climate-resilient, sustainable conservation strategies to ensure the long-term protection of the species.

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