

Integrating ecological niche modeling and land use analysis for targeted conservation of *Elaeocarpus prunifolius* in India

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Abstract

Mismatch between broad spatial scales at which niche models operate vis-à-vis the finer localized scales required for conservation actions often hinder the effective translation of model outputs into actionable strategies. This study addresses this issue by integrating ecological niche modelling (ENM) with land use and land cover (LULC) analysis to improve the conservation status of a threatened tree species *Elaeocarpus prunifolius* in Northeast India. Using the Maximum Entropy (Maxent) model, we predicted the potential distribution of *E. prunifolius* using MODIS-based Enhanced Vegetation Index (EVI) and ASTER-based elevation data. The predicted distribution, covering 8.97% (~ 201,321 ha) of Meghalaya's total geographical area, was further refined through the overlay of LULC maps, identifying ~ 17,033 ha as highly suitable habitat. Field validation of the predicted distribution maps led to the discovery of new populations, confirming the model accuracy. This integrated approach demonstrates the effectiveness of combining ENM with LULC analysis for the precise identification of conservation sites, thereby improving the potential for successful conservation and reintroduction efforts for *E. prunifolius*. The study highlights the critical role of integrating predictive models with ground validation in developing informed and effective conservation strategies.

Introduction

The impact of anthropogenic activities has led to significant threats to global forests, including fragmentation, over-exploitation, and habitat loss, which have collectively driven many species towards the brink of extinction (MEA 2005; Boonman et al. 2024). The consequences of these environmental pressures warrant the need for targeted conservation strategies (Rivers et al. 2022). Given the constraints on financial and human resources, the primary objective in conservation science is to prevent the extinction of threatened species (Barik et al. 2018). One of the major challenges in conserving these species is the limited knowledge regarding their occurrence and distribution (Schemske et al. 1994; Adhikari et al. 2018). Therefore, accurately locating potential habitats and understanding the geographical range of these species is essential for effective conservation efforts.

Recent advancements in remote sensing and space science have greatly enhanced the capacity to monitor forest landscapes. Ecological niche modelling (ENM) has emerged as a robust tool for estimating species distributions, identifying vulnerable habitats, and assessing the impacts of climate change (Adhikari et al. 2012; Jaryan et al. 2013; Abrha et al. 2018). These models predict potential distribution areas by correlating species occurrence records with environmental variables, offering a clearer ecological context. ENMs can significantly narrow down potential distribution sites and optimize field surveys that might otherwise be logistically challenging and resource-intensive (Menon et al. 2010).

Though ENM offers a powerful framework for identifying priority areas, the real challenge lies in effectively translating these insights into actionable, context-sensitive conservation strategies that are both targeted and sustainable. The spatial scale mismatch between niche models and conservation actions presents a significant challenge in biodiversity conservation (Iralu et al. 2023). Niche models are typically designed to operate over broad geographic scales, providing generalized predictions about species distributions based on environmental variables. These models are invaluable for identifying potential habitats and assessing species' responses to large-scale changes, such as climate shifts. However, conservation actions often need to be implemented at much finer, localized scales where microhabitat conditions, species interactions, and site-specific threats are critical to the success of interventions (Boyd et al. 2007; Hu et al. 2019). This disparity in scale can result in difficulties when attempting to translate the broad predictions of niche models into specific, actionable conservation strategies. The broad-scale outputs may overlook critical local factors such as microclimatic conditions, land-use patterns, or the presence of key biotic interactions, leading to conservation efforts that are misaligned with the actual needs of the species at risk (Jiménez and Soberón 2022; Edwards-Calma et al. 2024). Therefore, bridging this scale mismatch is essential for ensuring that conservation strategies are both scientifically robust and practically effective.

We believe that the integration of ecological niche modelling outputs with land use analysis can meaningfully help in conservation of threatened species with highly restricted distribution. Ecological niche modelling predicts the potential distribution of threatened plants by identifying environmental conditions and geographic areas that are most suitable for its growth and survival. Land use analysis helps to assess the current landscape and human activities that may impact these potential habitats. By overlaying niche model predictions with land use data, conservation planners can identify areas where suitable habitats overlap with regions of low human disturbance or where land-use change is minimal. Thus, these broad-scale predictions coupled with land use analysis can translate into on-the-ground conservation actions. This approach may ensure that conservation efforts are not only focused on areas that are ecologically suitable but also on those that are viable for protection or restoration in the context of human activities.

In this study, we demonstrate the above concept using the case of *Elaeocarpus prunifolius*, which is a rare and threatened tree species in Northeast India. The objectives of the study are: (i) to map the potential distribution of *Elaeocarpus prunifolius* in Meghalaya, (ii) to characterize potential habitats for rehabilitation and reintroduction efforts, and (iii) to evaluate the current population status in Meghalaya.

Materials and methods

About the species

E. prunifolius is reported from Manipur, Meghalaya, and Bangladesh, classified as 'Vulnerable B1 + 2c' (Murti 1993a,b; World Conservation and Monitoring Centre 1998). In Meghalaya, the species is rare, restricted to fragmented sub-tropical broad-leaved forests at elevations of 900–1800 m asl (Walter and Gillett 1998; Nayar and Sastry 1990). It faces extinction risk due to habitat degradation and over-exploitation of timber and edible fruits (Jain and Rao 1983; Haridasan and Rao 1985; Nayar and Sastry 1990). The species' seeds are dormant with low natural germination rates, contributing to its

rarity (Iralu and Upadhaya 2018). However, there is a significant lack of information on its distribution and population status in the wild (World Conservation and Monitoring Centre 1998).

Study area

The study was conducted in the state Meghalaya, India that lies between 89°49'E to 92°50'E longitude and 25°02'N to 26°07'N latitude in the northeastern biogeographic zone of India. The state covers an area of 22,429 km² and is a part of the Indo-Burma hotspot. Elevation ranges from 60 to 1990 m asl (SER 2005; Haridasan and Rao 1985). The major vegetation types are tropical semi-evergreen, tropical moist, tropical evergreen, dry deciduous, subtropical broad-leaved, subtropical pine forests and temperate forests (Champion and Seth 1968; Haridasan and Rao 1985).

Data collection and preparation

Extensive field surveys were conducted during 2014–2018. A total of 150 occurrence points (latitude and longitude) of *E. prunifolius* were collected from Khasi and Jaintia hills of Meghalaya using a Garmin global positioning system (GPS). The data points were further converted to decimal degrees for modelling purposes.

Environmental variables

For modelling, we utilized elevation and the enhanced vegetation index (EVI) to map potential habitats for the species. Elevation data was sourced from the digital elevation model (DEM) with a 90-meter spatial resolution, available on the United States Geological Survey (USGS) website (www.srtm.usgs.gov). Vegetation in a geographical area is shaped by various environmental factors, including climate, soil characteristics, and geology (Soleimani et al. 2008). These influences are reflected in the variation of greenness indices like normalized difference vegetation index (NDVI) and EVI, making these indices valuable for modeling purposes (Setiawan et al. 2014; Adhikari et al. 2018). Twenty-three EVI images from the moderate resolution imaging spectroradiometer (MODIS), with a formula of $EVI = 2.5 * (NIR - RED) / (NIR + 6.0 * RED - 7.5 * BLUE + 1.0)$ and a spatial resolution of 250 meters, were acquired from the USGS site (<https://lpdaacsvc.cr.usgs.gov/appears/>). These images capture the spatial and temporal variations in EVI at fortnightly intervals throughout 2015, coinciding with extensive field study to locate the species. A subset of the study area, along with a 1 km buffer, was delineated using a polygon that encompassed all occurrence points. The EVI data for the study area were then extracted using this polygon as the area of interest. The extracted data were resampled to a 250 m spatial resolution and converted to ASCII grids for modeling potential habitats. To prevent cross-correlation among environmental variables, a correlation test was performed using ENM Tools 1.3 and variables showing high correlation ($r > 0.8$) viz. EVI_2, EVI_5, EVI_17, EVI_18, EVI_19, EVI_20, EVI_21, EVI_22, EVI_23. were eliminated following Warren et al. (2010).

Model development and calibration

We used Maxent software, version 3.3.3k, to predict the distribution of the species. The software was freely downloaded from <http://www.cs.princeton.edu>. After removing duplicate presence records, we retained 61 unique records. Of these, we utilized 70% for model training and reserved 30% for testing. To validate our model, we conducted 10 replicate runs using a threshold rule of the 10-percentile training presence and averaging the results. The model was parameterized with 10,000 background points, 500 iterations, and a convergence threshold of 0.00001 (Phillips and Dudik 2008). To avoid over-fitting, the default regularization multiplier of 1 was applied. We maintained cross-validation by dividing the samples into replicate folds, with each fold used as test data. Given that the presence record of the species was greater than 15 and lesser than 79, we used hinge, linear, and quadratic features to optimize model complexity (Adhikari et al. 2012). The relative influence of predictor variables in the model output were evaluated by performing jackknife tests and analyzing the percent variable contribution (Phillips et al. 2006).

Model performance was evaluated based on the area under the curve (AUC) value and the receiver operating characteristics (ROC) metrics (Fielding and Bell 1997). An AUC value below 0.5 indicates a poor model, while an AUC of 1.0 signifies perfect discrimination. Model quality was classified based on AUC values following the guidelines proposed of Thuiller et al. (2005a, b) as: poor ($AUC < 0.8$), fair ($0.8 < AUC < 0.9$), good ($0.9 < AUC < 0.95$), and very good ($0.95 < AUC < 1.0$). The species distribution was re-classed based on the threshold of '10 percentile training presence' as very high (0.805–1) and high (0.612–0.805) clubbed under the general category 'High', medium (0.419–0.612), low (0.226–0.419) and very low (0.000–0.216).

The partial AUC metric, which measures the average sensitivity over a fixed range of the false positive rate was applied to ensure model consistency (Lobo et al. 2008; Peterson et al. 2008). We estimated the Partial AUC using Niche Toolbox, an online tool available at <http://shiny.conabio.gob.mx:3838/nichetoolb2/>. The ratio between the random AUC (set at the 0.5 level) and the partial AUC (with a defined omission level of 0.05) was calculated using the occurrence data and the predicted distribution model. 500 bootstrap iterations with 5% omission were executed to obtain the distribution curves. The graphical distribution output of the estimated AUC_{random} and AUC_{actual} was derived along with *t*-tests for the difference between the distributions (Lobo et al. 2008). Additionally, jackknife tests and relative percent variable contribution were used to identify the variables influencing the model output (Phillips et al. 2006).

Land use land cover mapping for identification of suitable habitats

Land use land cover (LULC) map for the study area was created using six Landsat satellite images (L8 OLI/TIRS) with a spatial resolution of 30 meters and less than 10% cloud cover were downloaded from <https://earthexplorer.usgs.gov>. The scenes correspond to the study period of 2015–2017 for December and January. A false-color composite (FCC) for vegetation cover was generated (bands- B3-Green, B4-Red and B5-Near Infra-Red) and a supervised classification was developed. The accuracy of the LULC maps were assessed through ground truthing and using Google Earth images. Eight LULC classes viz., dense vegetation, sparse vegetation, plantations, settlements, water bodies, degraded areas, mining sites, and sediments were identified. In this study, we distinguished between sparse and dense vegetation using the DN values from the FCC of the LULC map. Ground validation identified sparse vegetation along forest edges and canopy gaps within the forests. Finally, the predicted Maxent-based species distribution potential area distribution map was superimposed on the LULC map to identify and extract the areas having high suitability. Mapping and area estimation for the various land use classes were carried out using Q-GIS and ArcMap.

Population structure and regeneration status

For population studies, extensive field surveys were carried out in parts Meghalaya's Khasi and Jaintia hills where Maxent model predicted potential distribution of *E. prunifolius*. A belt transect of 20 m wide and 250 m long (0.5 ha) was laid in each study site which was further divided into 10 x 10 m quadrats for systematic sampling. All adult individuals of ≥ 5 cm diameter at breast height (dbh) were counted and measured. For saplings (< 5 cm dbh and > 1 m height) and seedlings (< 1 m height), 5 x 5 m and 2 x 2 m quadrats were laid in the center of the quadrats that were used for enumeration of adult individuals. The state of regeneration was assessed by categorizing them as good (if seedling $>$ sapling $>$ adult); fair (if seedling $>$ sapling $\leq$ adult); poor (if no individuals in the seedling stage), none (if individuals in the seedling and sapling stages were absent) and new (if no adult individuals were found) (Sukumar et al. 1992). Based on the species distribution model and the current population status, areas classified as medium to very high potential zones with ≥ 5 ha having ≤ 5 adult individuals, were identified as probable sites for reintroduction (Iralu et al. 2023).

Results

Model performance

The Maxent model calibrated for *E. prunifolius* showed strong predictive performance with an AUC_{training} and AUC_{test} values of 0.980 and 0.968, respectively. The partial AUC test demonstrated the Maxent model's high predictive capacity, accurately distinguishing true presence from false presence. Both ROC_{full} and ROC_{partial} showed high AUC scores (0.97 ± 0.001 and 0.97 ± 0.005 , respectively). Additionally, the AUC ratios ($AUC_{\text{partial}}/AUC_{\text{random}}$) derived from bootstrap values were significantly higher than random expectations, indicating excellent model consistency (Fig. 1).

Niche characterization

The jackknife test for variable importance indicated that elevation was the most significant contributor to the distribution model, accounting for 51.4%. Out of the 13 EVI layers used, EVI layers 11, 9 and 16 contributed the highest with 17.5%, 8.7% and 7.9% to the model development, respectively. This period aligns with Meghalaya's monsoon season and the species' fruiting period (Iralu and Upadhaya, 2015). Elevation with a permutation importance of 71.4% contributed the greatest influence on the model and EVI layers 11, 9 and 16 together contributed 18.2% (Table 1).

Table 1
Environmental variables used for building the model and their relative contributions and permutation importance

Predictor Variable	Percent contribution	Permutation importance
Elevation	51.4	71.4
EVI_11 (26 June-11 July)	17.5	9
EVI_9 (25 May-9 June)	8.7	3.1
EVI_16 (14 Sept-29 Sept)	7.9	6.1
EVI_4 (6 March-21 March)	5	1.7
EVI_14 (13 Aug-28 August)	3.2	2.3
EVI_8 (9 May-24 May)	1.7	0.5
EVI_13 (28 July-12 August)	1.4	0.6
EVI_7 (23 Apr-8 May)	0.9	3
EVI_15 (29 Aug-13 Sept)	0.8	0.2
EVI (Jan 1-Jan 16)	0.7	1
EVI_10 (10 June – 25 June)	0.5	0.6
EVI_12 (12 July-27 July)	0.3	0.3
EVI_3 (18 Feb-5 Mar)	0.1	0.2

Current potential habitat distribution

The habitat distribution model indicated that 8.97% (201321 ha) of Meghalaya's total geographical area is potentially suitable for *E. prunifolius*. Of this area, 0.10% is classified as very high potential, 0.97% as high potential, 2.48% as medium potential and 5.42% as low potential. The distribution was observed to be spread across the Khasi and Jaintia Hills with a narrow belt of potential distribution zone in Garo Hills. The elevation of the species distribution was 700–1500 m asl (Fig. 2).

Model prediction in relation to population density

To evaluate the efficacy of the Maxent model in predicting potential zones for species distribution, we compared the population of the studied species at each site to the model's habitat suitability predictions. Among the 43 sites where the species was present, 9 were classified as very high potential, 13 as high potential, 10 as medium potential, and 11 as low potential. The average density of trees, saplings, and seedlings was highest in the high potential zone (73 individuals), followed by the very high potential zone (59 individuals). The medium and low potential zones had average densities of 49 and 36 individuals, respectively. One-way ANOVA results indicated no significant variation ($p > 0.05$) in the population of adult individuals across the suitability classes, though higher numbers were observed in the higher potential zones (Table 2).

Table 2
The mean number of individuals of *E. prunifolius* under the habitat suitability classes

Suitability class	<i>E. prunifolius</i>				
	No. of sites	AD	SP	SD	Total
Very high	9	6	21	32	59
High	13	8	25	39	72
Medium	10	6	17	26	49
Low	11	5	13	18	36
AD-Adults; SP- Saplings; SD- Seedlings.					
Means followed by the same letter do not differ significantly at $p < 0.05$ (Scheffe's test).					

Habitat characterization for species reintroduction

For estimating suitable areas for species conservation and reintroduction, only regions predicted to have very high and high suitability were considered. *E. prunifolius* was predicted to be present in 8 out of the 11 districts of Meghalaya, specifically in East Jaintia Hills (EJH), West Jaintia Hills (WJH), East Khasi Hills (EKH), West Khasi Hills (WKH), South-West Khasi Hills (SWKH), East Garo Hills (EGH), and West Garo Hills (WGH). Overlaying the very high and high suitability areas on the LULC map revealed that the East Khasi Hills (EKH) district had the largest suitable area for species distribution, totaling approximately 10,361 hectares. Of this, 4,897 hectares were dense forest, and 3,154 hectares were sparse vegetation. The district also experienced the

highest level of anthropogenic activities in the predicted areas, with expanding settlements covering 347 hectares, plantations covering 261 hectares, and mining activities covering 120 hectares. In the West Jaintia Hills (WJH) and East Jaintia Hills (EJH) districts, suitable areas under vegetation cover were 3,749 hectares and 4,565 hectares, respectively. The vegetation cover in WJH (1,532 hectares) was relatively lower than in EJH (3,426 hectares), with 50% (1,850 hectares) of land in WJH being either degraded or barren. Approximately 329 hectares of the suitable area were under settlements, plantations, agriculture, and mining. In South-West Khasi Hills (SWKH), 2,665 hectares of forest area fell within the species' suitable habitat. However, rapid anthropogenic activities, such as expanding settlements (96 hectares) and increasing plantations and agricultural areas (55 hectares), were evident. Although the predicted suitable areas in West Khasi Hills (WKH), East Garo Hills (EGH), and South Garo Hills (SGH) were relatively smaller than those in other districts, most of these areas were under dense or sparse vegetation with minimal anthropogenic activities. The West Garo Hills (WGH) had the lowest suitability, with only 154 hectares predicted as suitable habitat (Table 3, Fig. 3).

Districts	Potential distribution classes	Land-use classes																
		Dense vegetation		Sparse vegetation		Plantations		Settlements		Water		Degraded land		Mining		Sediments		Total area (ha)
		Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	
West Jaintia hills	Very High	144	29	94	19	29	6	22	4	4	1	195	39	8	2	3	1	499
	High	714	22	580	18	173	5	62	2	25	1	1655	51	35	1	6	0	3250
East Jaintia hills	Very High	314	92	11	3	1	0	3	1	0	0	11	3	0	0	0	0	340
	High	2661	63	440	10	94	2	72	2	24	1	919	22	7	0	8	0	4225
East Khasi hills	Very High	663	60	263	24	13	1	23	2	27	2	101	9	10	1	0	0	1100
	High	4234	46	2891	31	248	3	324	3	166	2	1283	14	110	1	5	0	9261
Southwest Khasi hills	Very High	156	51	89	29	1	0	7	2	8	3	45	15	0	0	1	0	307
	High	1273	37	1147	34	54	2	89	3	81	2	761	22	0	0	3	0	3408
West Khasi hills	Very High	3	75	1	25	-	-	-	-	-	-	-	-	-	-	-	-	4
	High	340	45	159	21	30	4	72	10	19	3	136	18	0	0	1	0	757
East Garo hills	Very High	6	55	5	45	-	-	-	-	-	-	-	-	-	-	-	-	11
	High	399	82	85	17	-	-	-	-	1	0	2	0	-	-	-	-	487
South Garo hills	Very High	5	71	2	29	-	-	-	-	-	-	-	-	-	-	-	-	7
	High	214	93	14	6	1	.4	-	-	-	-	-	-	-	-	-	-	229
West Garo hills	Very High	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
	High	122	79	8	5	1	1	1	1	-	-	22	14	-	-	-	-	154
Very high and high potential		11245		5788		645		675		355		5130		170		27		Total-24035

Based on the species distribution model and the current population status, the sites for reintroduction of the species have been suggested in the following sites namely Lum Shynna, Lawbah Arliang, Sai Mika forest, Tyllong Um-Kyrwiang, Wah Bah Pomolang, Law Shnong Umladkur 3, Law Shnong Umladkur 7, Krang Suri forest, Law Shnong Umladkur 4, Law Siarpa, Law Syiem Ramakrishna Mission and Law Shnong Amlarem.

Population density in relation to forest size and disturbance

A correlation analysis of population density with forest area revealed no significant relationship between the number of adults and forest patch size ($p = 0.824$). However, a positive linear trend was noted for the populations of saplings ($p = 0.528$) and seedlings ($p = 0.258$) in relation to forest size, although this trend was not statistically significant. Further analysis of population density in relation to environmental disturbance showed a weak positive correlation for adults ($p = 0.550$), saplings ($p = 0.613$), and seedlings ($p = 0.568$), suggesting the species ability to tolerate environmental disturbances. Nevertheless, the population and regeneration of the species have been severely impacted by fruit extraction and selective logging for construction purposes in the regions where it occurs.

Population and regeneration status

The population density varied widely among the study sites. A total of 2,355 individuals were recorded across four districts (WKH, WJH, EKH, SWKH), comprising 275 adults, 828 saplings and 1,252 seedlings (Table 4). The highest number of adult trees was recorded from Law Shnong Umladkur 1 with 16 individuals. The sites namely Raliang Khlo Lyngdoh and Wah U Dkhar had 1 adult individual each and no adult individuals were recorded from Law Siarpa. The regeneration status of the studied species, based on the number of adults, saplings, and seedlings, varied across the sites. Out of the 43

sites, 28 exhibited 'good' regeneration, 9 had 'fair' regeneration, 3 showed 'poor' regeneration, 2 had 'none,' and 1 site displayed 'new' regeneration (Table 4). Law Sparba recorded the highest number of individuals (154), consisting of 15 adults, 52 saplings, and 87 seedlings. Conversely, Wah Bah Pomolang had the lowest count, with only 3 adults and no saplings or seedlings. Law Shnong Umladkur 1 had the highest number of adults (16), Law Adong Mawkyrnot had the highest number of saplings (53), and Law Sparba had the highest number of seedlings (87). The absence of saplings and seedlings in sites namely Krang Suri Forest, Wah Bah Pomolang, Kyrmia Sorkar, Law Lyngdoh Mawphlang, and Wah U Dkhar indicates a declining population in these areas (Table 4).

Discussion

The selection of appropriate environmental variables and algorithms is critical in accurately modeling species distributions. In this study, enhanced vegetation index (EVI) and elevation data effectively predicted suitable habitats for *E. prunifolius*, achieving an AUC_{partial} value of 0.97, categorizing it as an 'excellent' model (Swets, 1988). Elevation emerged as a crucial variable, reflecting the species' observed distribution across 600–1800 m asl elevations. The influence of various environmental factors, such as climate, soil characteristics, and geology, on regional vegetation patterns is well-documented (Soleimani et al. 2008). These factors are often captured by variations in greenness indexes, making such indexes valuable for species distribution modeling (Kulloli and Kumar 2014). The EVI, known for its sensitivity to greenness in humid forests and its ability to detect vegetation changes across spatial and temporal scales, was an excellent predictor in this study (Huete et al. 1999; Setiawan et al. 2014). Specifically, the EVI layers from May, June, July, and September, along with elevation, contributed over 80% to the species distribution models, coinciding with the fruiting period of *E. prunifolius* as indicated by the phenological calendar (Iralu and Upadhaya 2018). These findings show the importance of selecting relevant environmental variables that align closely with the species' ecological and phenological characteristics, thereby enhancing the model's predictive accuracy and its utility for targeted conservation efforts.

Table 4
Habitat characteristics, population density and regeneration status of *E. prunifolius* in Meghalaya

Occurrence sites	Suitability class	Ele	Asp	Area (ha)	Adl	Sap	Sdl	Total	Reg. status	Current disturbances
West Khasi Hills (WKH)										
Law Siarpa	Medium	1398	SE	9.21	0	5	3	8	New	Grazing, road construction,
West Jaintia Hills (WJH)										
Law Shnong Umladkur 1	High	1134	S	13.6	16	47	62	125	Good	Extraction of fuel wood and NTFPs, grazing, road construction, water reservoir construction
Law Shnong Umladkur 2	High	1118	SW	6.3	6	6	23	35	Fair	Extraction of fuel wood and NTFPs, road construction, grazing
Law Shnong Umladkur 3	High	1108	SW	38	3	12	15	30	Good	Extraction of timber and fuelwood, grazing, construction of road
Law Shnong Umladkur 4	Medium	1123	S	6	3	9	11	23	Good	Extraction of timber and fuel wood, grazing, road construction, settlements
Law Shnong Umladkur 5	Medium	1130	S	8.6	12	38	41	91	Good	Extraction of fuel wood, construction of road, settlements
Law Shnong Umladkur 6	High	1131	S	22.5	9	32	44	85	Good	Settlements, road construction, sandstone mining
Law Shnong Umladkur 7	High	1121	SW	8.8	3	3	11	17	Fair	Extraction of fuel wood and NTFPs, grazing, road construction, settlements
Law Shnong Amrawan	High	1169	W	105	9	33	83	125	Good	Plantations, grazing, road and footpath construction, settlements, graveyard
Law Shnong Amlarem 1	Medium	908	S	24.7	5	11	17	33	Good	Construction of road, sandstone mining
Law Shnong Amlarem 2	Medium	956	SE	24	6	15	16	37	Good	Construction of road, sandstone mining
Krang Suri forest	High	983	E	10.7	4	9	0	13	Poor	Small footpath cutting through the forest
Kyrmia Sorkar	Low	608	SE	48.8	3	5	0	8	Poor	Relatively undisturbed
Raliang Khlo Lyngdoh	Low	1287	S	18.2	1	2	2	22	Fair	Extraction of timber and fuelwood, agriculture, road construction, settlements
Khlo Blai Ryngkaw	Low	1182	S	56.4	2	5	8	15	Good	Extraction of fuel wood, agriculture, settlements
East Khasi Hills (EKH)										
Law Lyngdoh Mawphlang	Low	1803	S	82.6	2	6	0	8	Poor	Relatively undisturbed
Tyrsad Law Adong	Low	1575	E	17	3	11	14	28	Good	Agriculture, road construction, settlements
Law Ander Mawrapat	Very high	1120	S	30.6	9	34	53	96	Good	Extraction of timber, fuel wood and NTFPs, agriculture, road construction, settlements
Law adong Laitsohum	Very high	1287	NW	33.7	6	29	32	67	Good	Extraction of fuel wood and NTFPs, agriculture, road construction, settlements
Law Adong Mawsynram village	High	1437	SE	12.9	8	41	53	102	Good	Extraction of timber, and fuel wood, road construction, settlements
Lawbah Forest	High	953	S	29.9	10	38	49	97	Good	Extraction of fuel wood and NTFPs, road construction, settlements
Wah Sier Swer	Low	1795	E	25.4	5	15	19	39	Good	Road construction, mining
Law Adong Phlangwanbroi	Medium	972	SW	12	9	35	49	93	Good	Road construction, settlements
Law Shnong	Very high	1148	S	8.8	10	6	10	26	Fair	Extraction of fuel wood, road

Occurrence sites	Suitability class	Ele	Asp	Area (ha)	Adl	Sap	Sdl	Total	Reg. status	Current disturbances
West Khasi Hills (WKH)										
Mawkasain										construction, settlements
Law Kyntang Lynshing	Medium	1535	NW	50.7	6	6	17	29	Fair	Relatively undisturbed
Law Adong Saitbakon	Low	1046	East	23.1	4	4	13	21	Fair	Extraction of timber, fuel wood and NTFPs, grazing, road construction, settlements
Law Adong mawkyrnot	High	1324	NW	39.6	15	53	82	150	Good	Relatively undisturbed
Law Adong Ureksew	Low	1304	NE	86.9	9	29	35	73	Fair	Extraction of timber and fuel wood, road construction, settlements
Law Sparba	Very high	1084	S	9.19	15	52	87	154	Good	Highway cuts through the forest
Law Adong Pongtung	Low	783	SE	10.3	15	31	49	95	Good	Road construction, settlements
Sai Mika forest	Very high	1363	NW	38.7	4	14	17	35	Good	Relatively undisturbed
Maw Ka Duia	High	1374	SE	2.1	3	12	20	35	Good	Extraction of fuel wood, road construction, settlements
Law Nongrim	High	1390	E	6.8	12	41	69	122	Good	Extraction of timber, fuel wood and NTFPs, grazing, road construction, settlements
Thang U Niaw	Medium	1321	NE	2.4	5	5	13	23	Fair	Extraction of timber, road construction, settlements
Wah U Dkhar	Very high	1380	E	4.1	1	0	0	1	None	Extraction of timber, fuel wood and NTFPs, grazing, road construction, settlements
Law Syiem Ramakrishna Mission	Medium	1350	NW	9.7	2	8	16	26	Good	Extraction of fuel wood, grazing, road construction, settlements
Wah Bah Pomolang	High	1312	S	7.1	3	0	0	3	None	Extraction of timber, fuel wood and NTFPs, road construction, settlements
Law adong Laitkynsew	Low	896	S	33.5	9	25	36	70	Good	Extraction of timber, fuel wood and NTFPs, road construction
Lum Shynna	Very high	1551	E	5.6	3	17	31	51	Good	Relatively undisturbed
Lawbah Arliang	Very high	1303	S	9.9	4	19	25	48	Good	Construction of road
Law Adong Lyngiong	Low	1752	S	14.3	5	5	22	32	Fair	Fuel wood extraction, agriculture
South-west Khasi Hills (SWKH)										
Tyllong Um-Kyrwiang	Very high	1457	SW	61.6	5	19	32	56	Good	Relatively undisturbed
Diri Mawranglang	Medium	1491	NW	60.4	11	41	73	125	Good	Agriculture, settlements
Ele- elevation, Asp- aspect, Adl- adult, Sap- sapling, Sdl- seedling, Reg. Status- regeneration status, E- east, W- west, S- south, N- north										

Earlier studies highlight the critical role of phenology in shaping the ecological niche of perennial plants (Morin et al. 2007; Chuine 2010). Plants synchronize their phenological cycles with their local environment by responding to key factors such as light, temperature, photoperiod, and water availability, thereby optimizing their periods of growth, flowering, and reproduction (Badeck et al. 2004; Chuine 2010). The timing of flowering and fruit ripening can evolve in response to selective pressures like temperature fluctuations and water availability (Lacey et al. 2003). Flowering time has been identified as a crucial determinant of species distribution, with studies showing that species within similar ecoregions often develop analogous phenological patterns (Thuiller et al. 2005a; Adhikari et al. 2018). For *E. prunifolius*, fruit development occurs from May to September, aligning with the wet season. This synchronization with the wet season is common among species that produce fleshy fruits, as observed in the subtropical forests of northeast India (Shukla and Ramakrishnan 1982; Kikim and Yadava 2001). Such timing allows for a trade-off where early flowering maximizes fruit set while minimizing the risk of frost damage to reproductive organs (Chuine 2010). The interplay between rising temperatures and increased moisture levels further influences the phenological patterns, significantly affecting the potential habitat distribution of *E. prunifolius*. Given this, many researchers advocate for incorporating phenological data into species distribution models to enhance their predictive accuracy (Chuine 2010; Ponti and Sannolo 2022; Peng et al. 2024).

Integrating Maxent model predictions with the land use and land cover (LULC) map has allowed for a more precise identification of habitats and land uses within the environmental matrix. This has enabled the targeted pinpointing of forest regions classified as suitable habitats for conservation and rehabilitation. Dense and sparse vegetation areas were identified as the most suitable habitats, with 17,033 hectares classified under 'very high' and 'high' suitability categories (Table 4). The highest concentrations of these suitable habitats were in the Khasi and Jaintia hills, highlighting the critical need to focus conservation efforts on these regions. Field observations and habitat characterization also revealed the presence of various anthropogenic activities within these areas, including human settlements, limestone mining, plantations, and extensive degraded lands. Given these pressures, it is crucial to prioritize the conservation of existing habitats to ensure the survival of this threatened species.

The Maxent model indicated that only 8.97% of Meghalaya's total geographical area is suitable habitat for *E. prunifolius*, emphasizing the urgent need to conserve the remaining habitat. Previous studies also suggest that integrating detailed land-use data or vegetation classifications significantly improves the accuracy of species distribution estimates (Sánchez-Cordero et al. 2005). To better understand habitat types and identify disturbances across the landscape, a land use and land cover (LULC) map was generated in the present study. This approach provided a quantitative estimate of the forest areas available for *in situ* conservation of the species. The model-based habitat characterization map revealed that the 'very high' and 'high' potential distribution areas encompassed 24,035 hectares, with 70% of this area consisting of dense and sparse vegetation. However, approximately 5,130 hectares (~ 21%) of the predicted area were degraded lands, while about 1,500 hectares were classified as plantations, settlements, and mining areas, rendering these sites unsuitable for conservation (Table 4). A positive relationship between species population density and the Maxent model threshold in the study indicated good model discrimination, with a higher number of individuals observed in the high potential zones compared to the medium and low potential zones (Table 4). The Maxent model has proven effective in identifying high suitability areas for other species as well, including *Rosa arabica* (Abdelaal et al. 2019), *Xanthium italicum* (Zhang et al. 2021), *Parnassia wightiana* (Dai et al. 2022), and *Ormosia microphylla* (Wei et al. 2024).

The size of forest seems to influence the population size of *E. prunifolius*, with a positive correlation observed between population density and forest area, although this relationship was not statistically significant ($p > 0.05$). Additionally, the relationship between the number of adult individuals and forest area was weak ($p = 0.824$). Field observations indicated that the species was present both at forest edges and within dense forests. *E. prunifolius* demonstrated greater resilience to disturbance and moisture stress compared to other associated species, such as *Magnolia punduana*, which were more sensitive to moisture stress (Iralu et al. 2023). Research has shown that edge effects also influence species populations, with forest fragments smaller than nine hectares likely dominated by edge patterns, while fragments smaller than one hectare may not support core forest conditions or vegetation associations (Young and Mitchell, 1994; Riutta et al. 2014).

The species' resilience is further evidenced by a weak positive relationship between population density and disturbance. *E. prunifolius* predominantly occupies canopy gaps created by selective logging and forest peripheries, indicating its tolerance to environmental disturbances and its light-demanding (heliophilic) nature. However, the species' high timber value makes it vulnerable to selective logging by local communities, posing a significant anthropogenic threat to its survival. Beyond human-induced disturbances, *E. prunifolius* populations are also influenced by environmental factors. Premature seed fall is a major constraint, with the fruiting period from May to September coinciding with the peak rainfall season in Meghalaya, averaging 565.83 ± 60.15 mm (2013–2017 data, <http://www.imd.gov.in/>). The fleshy mesocarp and nuts of mature fruits are further predated by small rodents, birds, worms, and ants. Additionally, the prolonged dormancy period of the seeds exposes them to predators for extended durations, further reducing recruitment (Iralu and Upadhya 2018). These factors contribute to the low recruitment rates observed in natural settings, a challenge also documented in other *Elaeocarpus* species (Matthew 1999).

Conclusion

Our study highlights the critical need for targeted conservation efforts to protect *E. prunifolius*, an endangered species with a limited and fragmented distribution in Meghalaya. The integration of Maxent modelling with detailed land use analysis provided valuable insights into the species' potential habitats and the challenges posed by anthropogenic activities. Despite the species' resilience to certain environmental disturbances, factors such as selective logging, habitat degradation, and seed predation significantly threaten its survival. Future research should focus on developing more robust models that can integrate diverse data types, enabling more precise identification of conservation areas. These efforts are essential for the effective management and preservation of *E. prunifolius* and similar threatened species in their natural habitats.

Declarations

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Figures

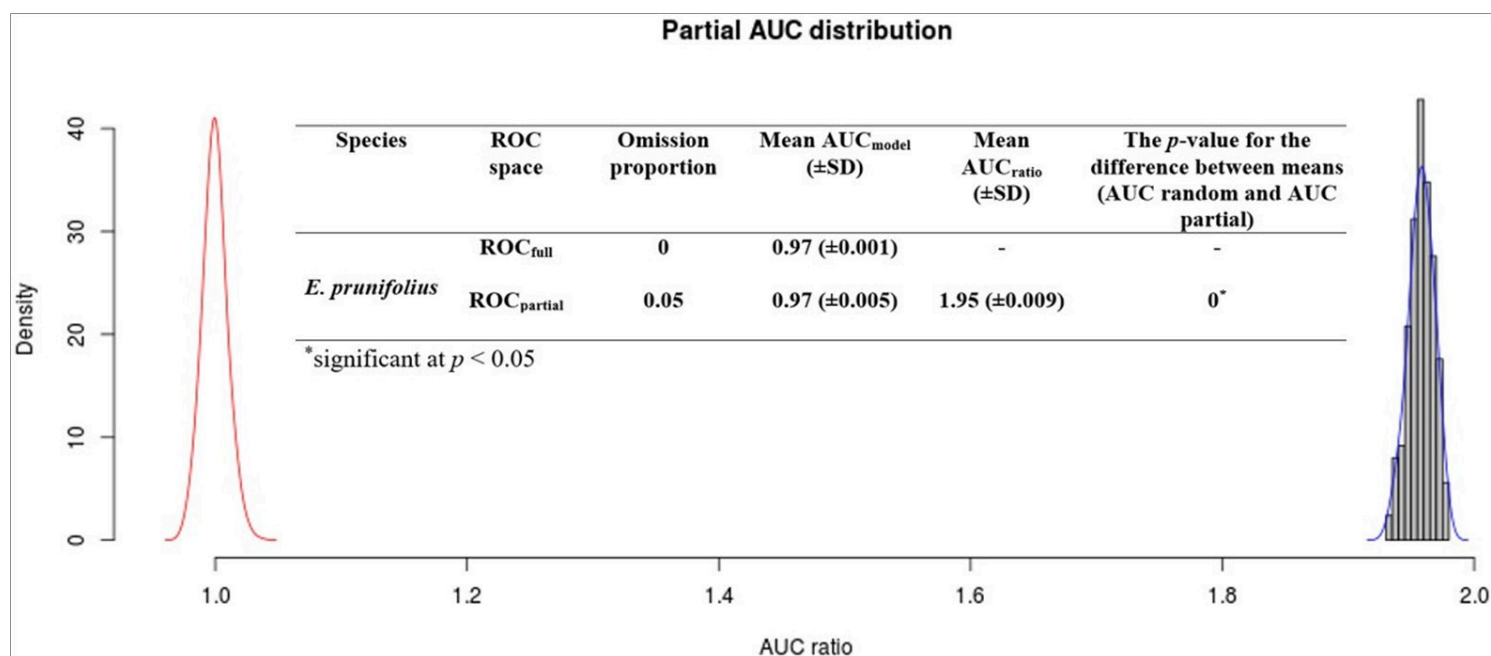


Figure 1

Graphical representation of partial AUC distribution of *E. prunifolius* calibrated with 500 iterations and 5% omission. The shaded curve on the right represents the frequency distribution of the ratios between AUC from model prediction and AUC_{random}. The curve on the left represents the distribution of AUC ratios for random models. The observed higher distributional range of AUC ratios for both the species indicates the better predictive ability of the Maxent model. The inset table presents the result of model evaluation tests done using full and partial ROC-AUC measures (The mean value for AUC at 0.5 is 0.5)

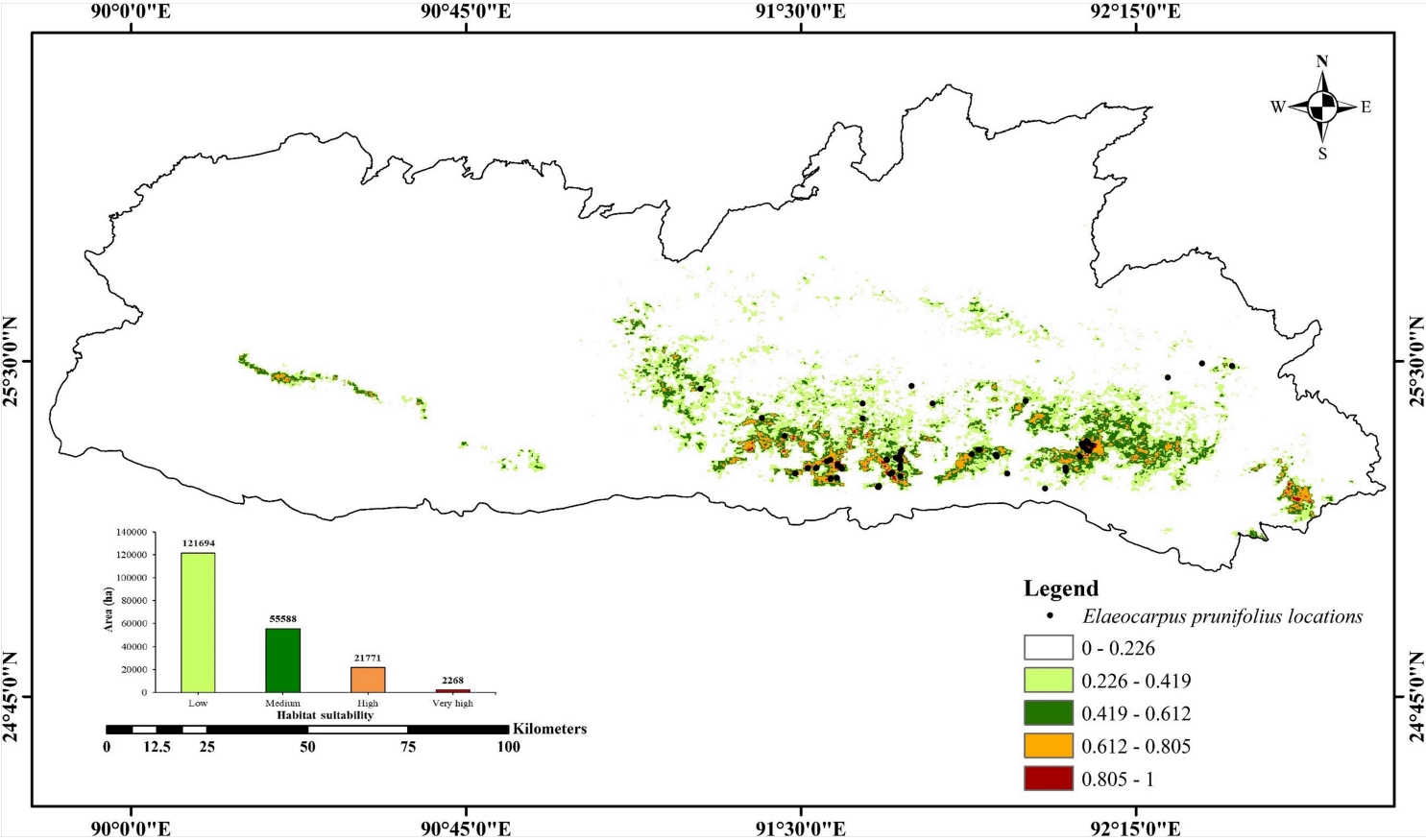


Figure 2

Map illustrating the potential habitat distribution of *E. prunifolius* in Meghalaya. Inset histogram shows the area under different habitat suitability classes (values on top represent area in hectares)

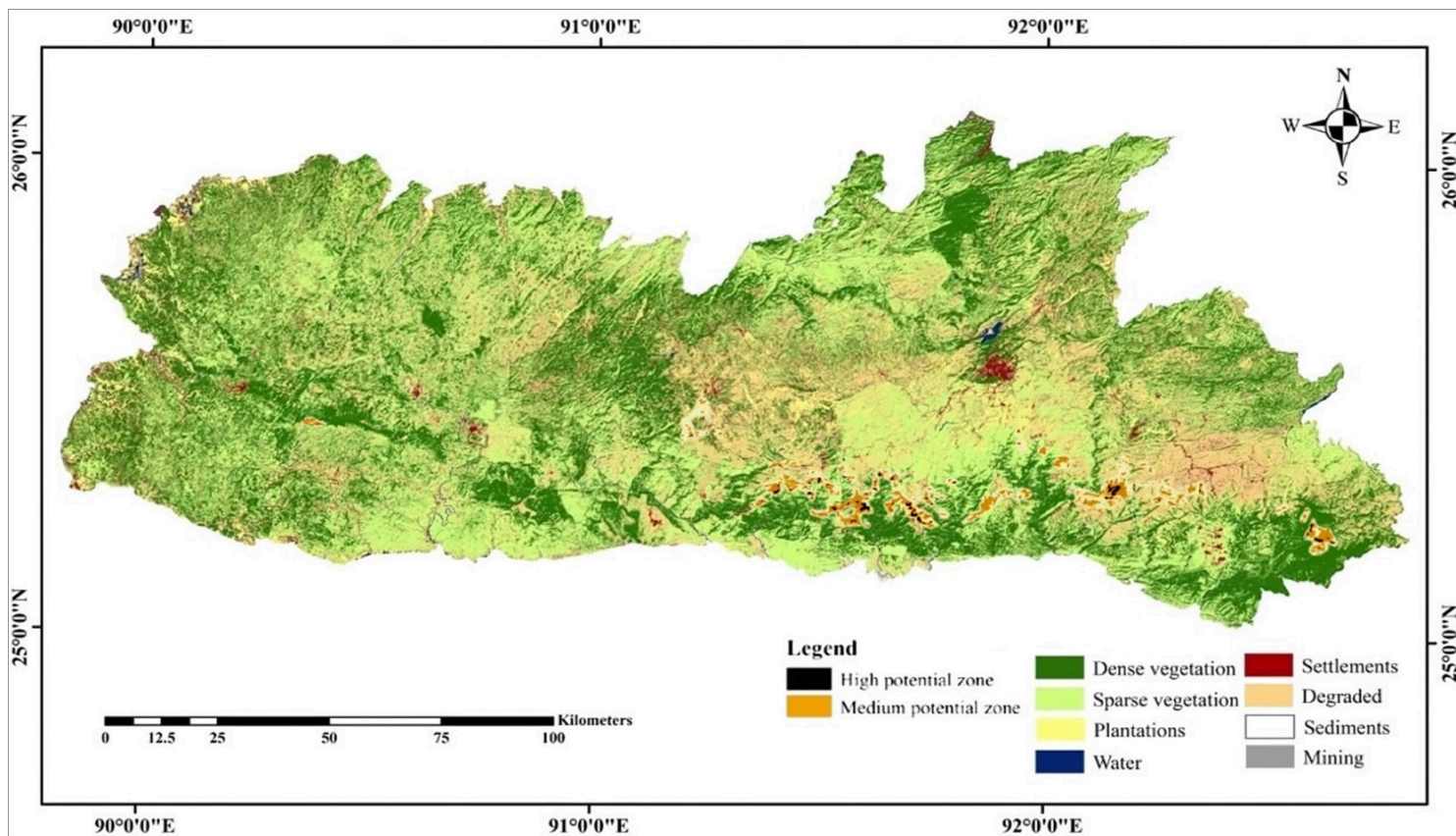


Figure 3

Map depicting the land use and land cover (LULC) of Meghalaya (2015–2018) highlighting the areas with 'high' (including very high and high) and medium potential distribution of *E. prunifolius*