Evaluating the Vulnerability of Threatened Tree Species to Global Drivers of Change in the Western Ghats

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Introduction

Tropical forests play a substantial role in maintaining planetary health. These ecosystems are exceptionally biodiverse, hosting half of all described species and many undescribed ones. They play a key role in regulating global biogeochemical cycles and contain approximately 40% of the global carbon stocks. In addition to contributing to a third of terrestrial net primary productivity, they also provide essential ecosystem services, including provisioning services such as food, water, fuel, timber; regulating services such as carbon sequestration and climate regulation; supporting services such as nutrient cycling and cultural services such as recreation.

India's Western Ghats (WG), a biodiversity hotspot, encompass a significant portion of the country's remaining tropical forests. Climatic and topographical gradients along the WG have led to diverse ecosystems and distinct assemblages of tree species (Karuppusamy, 2024). These assemblages exhibit high endemism—56% of the evergreen trees are endemic to the WG (Davidar et al., 2018). These trees also support unique biodiversity and provide valuable ecosystem services, such as pest management, pollination, and hydrological regulation, within the WG and to downstream communities throughout peninsular India.

However, the region has been undergoing considerable habitat loss (Myers et al., 2000) due to human pressures, including unsustainable agricultural practices, deforestation for agricultural purposes, and other developmental activities. As a result, several tree species of the WG are listed in the IUCN Red List of threatened species. Climate change is poised to exacerbate these changes by altering the distribution ranges of species and hindering critical ecosystem processes and services (Manes et al., 2021; Ravindranath et al., 1997). The loss of these tree species would impact the region's unique biodiversity, hamper ecosystem functioning and the ecosystem services people derive from these trees. Therefore, it is imperative to gain a good understanding of the factors that threaten the persistence of these tree species.

To achieve this, we applied a species-specific, spatially explicit vulnerability assessment method, developed by Gaisberger et al. (2017) and refined by Fremout et al. (2020), to 30 tree species native to the Western Ghats. We used species occurrence data to construct species distribution models (SDMs) for each species. These SDMs were combined with threat exposure maps and species functional trait data to assess their sensitivity and vulnerability to four key threats: overexploitation, fire, habitat conversion and climate change. Our findings provide critical, science-backed insights into the factors that threaten these species and can inform targeted restoration and conservation efforts.

Methods

Study Region

Our study region comprises the WG mountain chain of peninsular India, which runs parallel to the country's west coast, spanning six Indian states. Strong orographic effects on rainfall characterise the WG. These patterns drive seasonality gradients, which, combined with edaphic variations, have formed diverse and distinct vegetation types. The One Earth Bioregions Framework classifies the vegetation in the WG into three broad biomes—Tropical and Subtropical moist broadleaf forests, Tropical and Subtropical dry broadleaf forests and Deserts and Xeric shrublands *(One Earth Bioregions Framework, 2024).*

The WG also supports high human population densities, averaging 350 people per square kilometre (Cincotta et al., 2000). Large tracts of natural vegetation have been historically converted to anthropogenic land uses, with high rates of forest loss recorded between 1950 and 1990. On the other hand, thirty-nine protected areas (PAs) place varying levels of restrictions on human activity. However, most of these PAs are scattered across the WG, often occurring within a matrix of human use, limiting habitat connectivity.

We added a 25 km buffer to the WG for our study (Fig. 1) to account for ecological and landscape connectivity beyond the formal boundaries of the WG. We expect this buffer to help capture the transitional zones, environmental gradients and land use dynamics that influence species distributions.

Selection of tree species and compilation of occurrence records:

We used the list of 236 species from the Western Ghats incorporated into the Diversity for Restoration tool (**https://www.diversityforrestoration.org/tool/**) (Fremout et al., 2022) as a starting point for this study. From these, we selected species that are native to our study region, and collated occurrence records from peer-reviewed articles, open-access databases (e.g., GBIF), and other relevant sources. We thinned the occurrence data using a 1 km radius and selected species with at least 30 remaining occurrence records, which we considered the minimum number to obtain reliable distribution models (Wisz et al., 2008). Finally, we shortlisted 30 species that maximised the representation of vegetation types, range sizes, and phylogenetic and taxonomic diversity across the WG (Table 2). Additionally, these shortlisted species differ in their IUCN Red-List categorisation, allowing us to compare IUCN's assessments with ours. We assessed the vulnerability of the selected 30 tree species to four key threats: overexploitation, fire, habitat conversion and climate change.

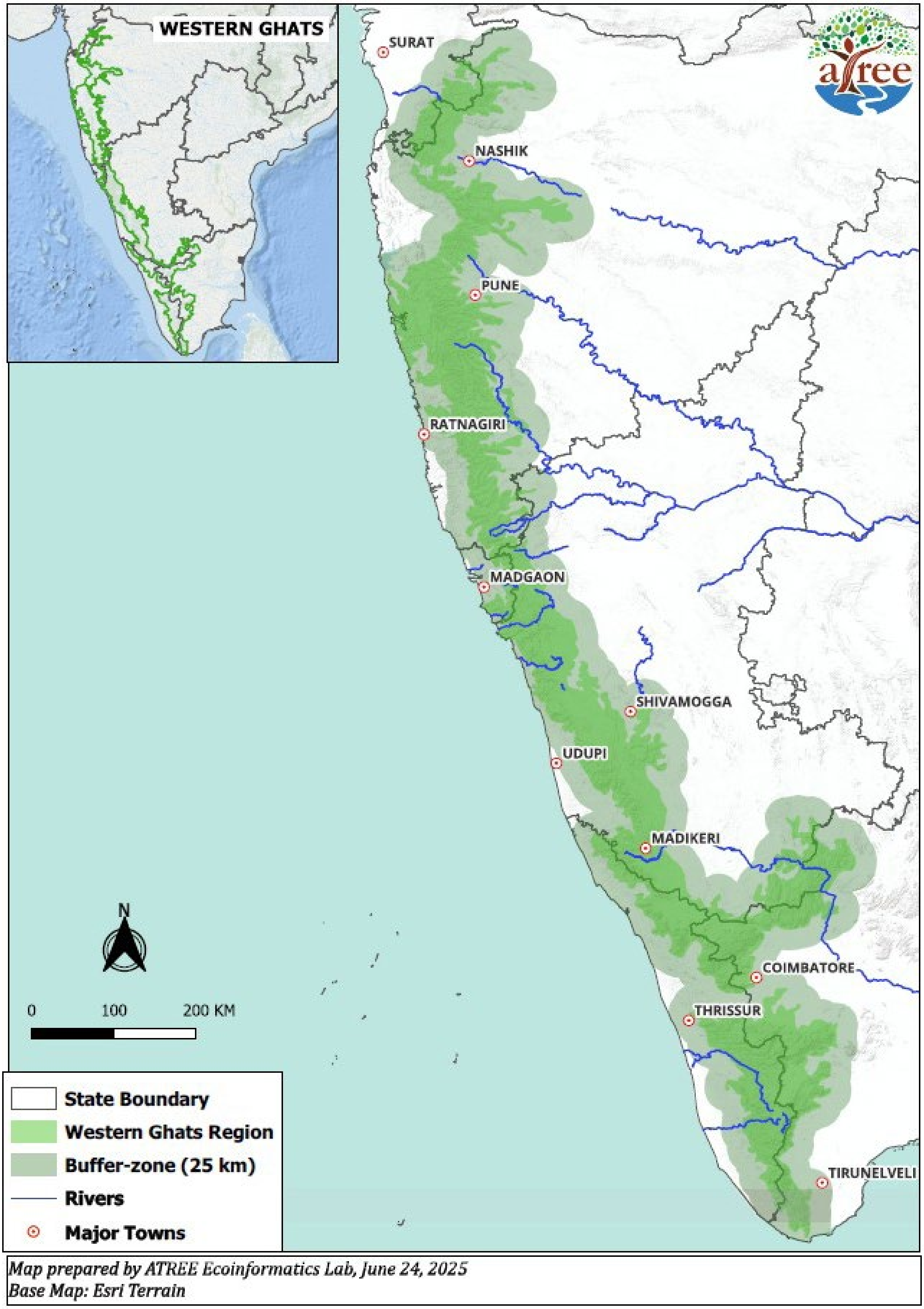

Figure 1: The Western Ghats biodiversity hotspot extends over six Indian states and is the source for several east-flowing and west-flowing peninsular rivers.

Species Distribution Modelling

We used the Maximum Entropy (MaxEnt) algorithm to build our SDMs. We utilised the raster (Hijmans, Etten, et al., 2025), sf (Pebesma & Bivand, 2023), and terra packages in R (Hijmans, Barbosa, et al., 2025) for viewing and processing our raster and vector data. We used the dismo (Hijmans et al., 2024) and ENMeval (Kass et al., 2025) packages for running MaxEnt, model tuning, model selection, and validation. We created a 30 arcsec sampling intensity grid (~1 km) using the occurrence records and following the target-group approach, randomly selected background points from this grid. This approach ensures that the background points represent the same spatial sampling bias as the occurrence records (Phillips et al., 2009). We selected 10,000 background points per species or the total number of cells from the sampling intensity grid, whichever was fewer.

We selected eleven bioclimatic layers, excluding those that combine temperature and precipitation and those that are inherently redundant. Our shortlisted predictor set (Supplementary Table 1) represents temperature and precipitation patterns, soil characteristics, and topographic features, either directly or indirectly. We systematically tested several model configurations, including various feature combinations for the response variables, such as Linear-Quadratic (LQ), Hinge (H), Linear-Quadratic-Hinge (LQH), and Linear-Quadratic-Hinge-Product (LQHP), as well as different regularisation multipliers (1, 3, and 5). For model validation, we performed cross-validation using spatial blocks created with the blockCV (Valavi et al., 2025) package in R, which enables spatial independence in our training and testing datasets. We use between 3 and 8 folds for cross-validating our models, depending on the availability of presence and background points. We then selected the optimal model for each species based on the cross-validated Area Under the Curve (AUC) statistics.

Creation of Threat Exposure Maps

We created threat exposure maps for climate change, fire, habitat conversion, and overexploitation, for reference, best-case, and worst-case scenarios, following the methodology developed by Fremout et al. (2020) and Ceccarelli (2022). The best-case scenario represents an optimistic view of species vulnerability, where even high exposure to threat has a minimal impact on species' vulnerability compared to the reference scenario. On the other hand, the worst-case scenario presents a pessimistic view, rendering species vulnerable even at lower values of threat exposure when compared to the reference scenario. The reference scenario itself represents a middle-of-the-road assessment that uses average threat exposure values obtained from literature to determine species vulnerability. These scenarios are meant to complement each other and represent alternative levels and exposure to threats that the selected species are vulnerable to.

We updated the methods of Fremout et al. (2020) and Ceccarelli et al. (2022) for determining exposure to climate change by using three Shared Socioeconomic Pathways (SSPs). Specifically, we used the ACCESS-CM2, GISS-E2-1-G, INM-CM5-0, MIROC6, and MPI-ESM1-2-HR GCMs under SSP126, SSP376, and SSP585 for the period 2040-2059, to create fifteen maps for each species. We also opted to assign different thresholds in fire exposure maps to reflect the differential adaptations of native tree species to fire in each WG biome. We set the maximum exposure to fire for Dry and Xeric shrublands and Tropical Dry Broadleaf forests at 10, 15 and 5 fires over a 5-year period for the reference, best-case and worst-case scenarios, respectively. Similarly, we set the maximum exposure to fire for Tropical Moist Broadleaf forests at 5, 10 and 3 fires over a 5-year period for the reference, best-case and worst-case scenarios, respectively.

We updated the overexploitation exposure layer by including distance to the nearest city as a variable, assuming that the market demand from these cities results in the higher exploitation of more proximate natural habitats. We obtained population density data at a 1 km resolution from the WorldPop dataset (**https://www.worldpop.org**/) for the year 2020. Studies have found that people in settlements up to 4 km from forests in the WG collect resources from these habitats (Davidar et al., 2008). To account for this, we calculated the population density value of each cell using a weighted average moving window of 9 × 9 cells, where the central cell was assigned the highest weight and cells further away were assigned lower weights. We rescaled the resulting layer to values between 0 and 1 by setting the maximum exposure to 732 people per sq. km. for the reference scenario (i.e. the 90th percentile of the WG's population density in the study region); 1090 persons per sq. km. for the best-case scenario (i.e. the 95th percentile of the WG's population density), and 462 persons per sq. km. for the worst-case scenario (i.e. the 80th percentile of the WG's population density).

We used the findings from Krishnadas et al. (2018) to set the maximum overexploitation as occurring within 4 km of a road and 22 km of an urban area. The best-case scenario threshold values were set at 2 km from a road and 11 km from an urban area, while the worst-case scenario threshold values were set at 8 km from a road and 33 km from an urban area. Based on these values, these proximity maps were rescaled from 0 to 1. We averaged these three exposure maps and adjusted the exposure values within protected areas accordingly using a multiplication factor of 0.25, 0.50, and 0.75 for the best-case, reference, and worst-case scenarios, respectively, following the approach outlined in Fremout (2020).

Finally, for the habitat conversion exposure map, we created a two-class current land-use land-cover (LULC) map consisting of anthropogenic and natural land use classes. We combined human-dominated land uses (plantations, agriculture, and built-up areas) from the Open Natural Ecosystems (ONE) map (**https://github.com/openlandcover/one7types**) with linear infrastructure (railways and powerlines), mines, and reservoirs from Geofabrik and the India Under Construction project (**https://indiaunderconstruction.com/**) to represent anthropogenic land use. We did not use roads because they were already included in the overexploitation layer. We also extracted forests, savannas, water, wetlands and bare ground from the ONE map to represent natural land use.

After this, we calculated the fragmentation of natural land use by anthropogenic land use to create our reference scenario and worst-case scenario layers for habitat conversion. We quantified fragmentation using a 3 × 3 moving window for the reference scenario, assuming that the proportion of anthropogenic LULC cells around a focal cell also influenced the exposure of that cell. For the worst-case scenario, we extended the effects of fragmentation using a 5 × 5 moving window. However, in these scenarios, anthropogenic land-use classes were always assigned a maximum exposure value of 1, regardless of the surrounding land use. We did not consider fragmentation in the best-case scenario, where all natural land use was assigned an exposure value of 0, indicating no threat, and all anthropogenic land use was assigned the maximum exposure value of 1.

Table 1:Summary of covariates and spatial layers used to estimate exposure to selected threats

Threat	Covariates quantifying threats	Spatial Layer Sources
Fire	Frequency of active fire occurrences between 2018-2020	NASA Fire Information for Resource Management System. MODIS Active Fire Detections 2018–2020 (Earth Science Data Systems, 2024)
Habitat Conversion	Grid cells were converted to anthropogenic classes, and the proportion of neighbouring grid cells converted to anthropogenic classes was assessed to assess the degree of fragmentation. Assessed using an LULC map containing ‘natural’ land-use classes (Forest, Savanna, Water/Wetland) and ‘anthropogenic’ classes (Plantations, Agriculture, Built-up area and Intrusions — Railways, Powerlines, Mines, Reservoirs)	Base LULC layer: Reclassification of existing mapping of India’s Open Natural Ecosystems (ONEs) (Madhusudan & Vanak, 2023) Intrusions: Geofabrik (Railways, Reservoirs) (OpenStreetMap contributors, 2017) and India under Construction (Mines, Powerlines) (Nayak et al., 2020)
Overexploitation	Human population density, Distance to nearest road, Distance to nearest city, Presence/absence of a Protected Area (PA)	WorldPop global human population density dataset (WorldPop, 2025); Geofabrik GIS dataset for roads and cities (OpenStreetMap contributors, 2017); India Under Construction PA dataset (Nayak et al., 2020)
Climate Change	Loss of modelled suitability between predicted distributions under current and future climatic distributions.	Suitability maps projected to future climate conditions using five global climate models and three Shared Socioeconomic Pathways (SSP126, SSP370, SSP585)

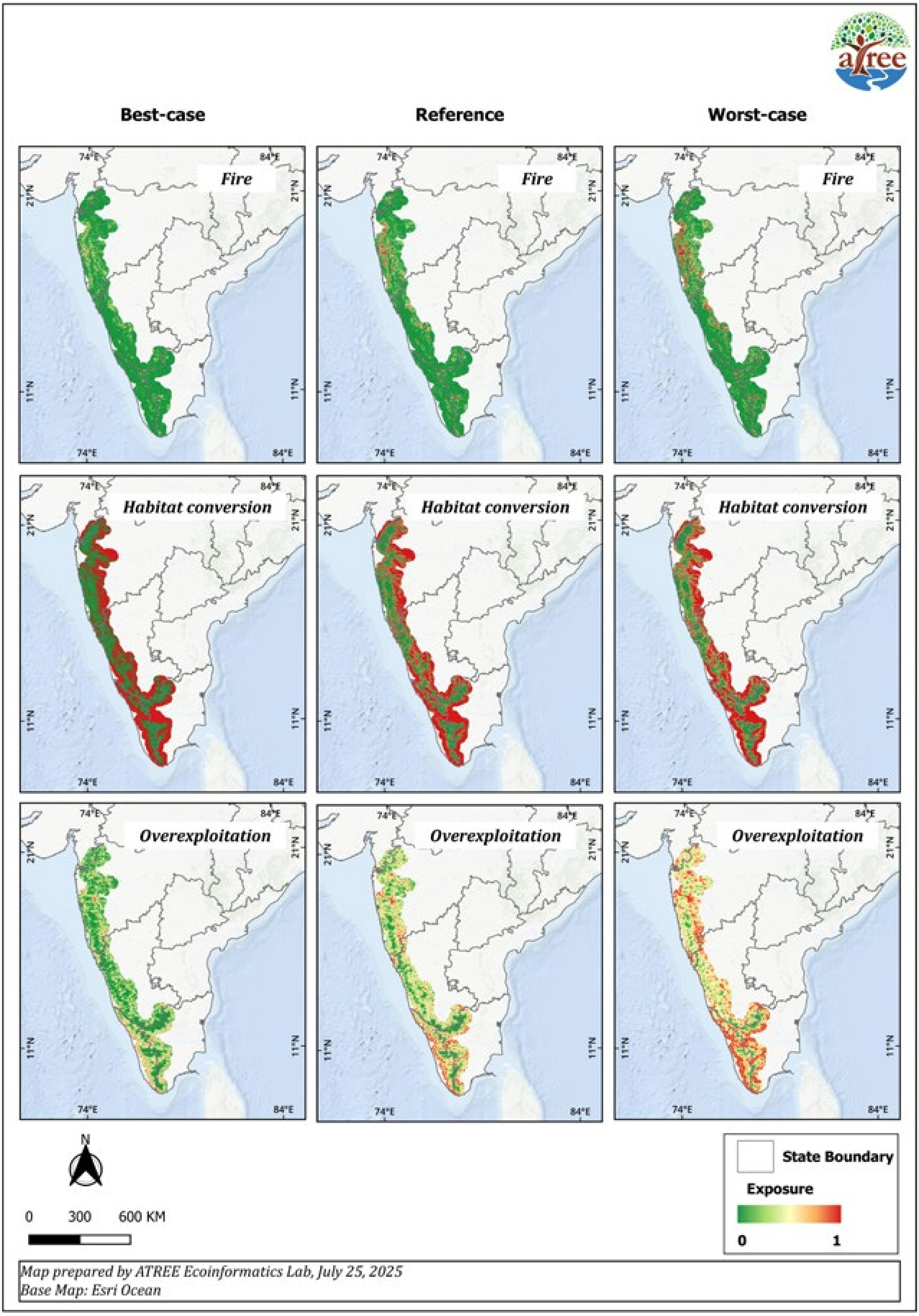

Figure 2: Exposure maps for individual threats (represented by rows), for each of the three scenarios:best-case, reference and worst-case (represented by columns)

Assessing Species Sensitivity and Threat Vulnerability Values

We utilised the species-specific threat sensitivity values provided by Ceccarelli et al. (2020). These values integrate species trait data with expert-informed trait weights for our four threats: climate change, habitat conversion, overexploitation, and fire (Supplementary Table 2). Each trait is assigned a weight for each threat, based on its relevance in determining a plant's response to that threat (see Figure 3 for an explanation and example). Then, each species is assigned a weighted sensitivity score for each threat based on its trait values. The weighted average of the trait weights multiplied by the sensitivity scores for each threat determines the sensitivity of a species to that threat. We then generated spatial vulnerability maps by combining species-specific threat sensitivity values and the threat exposure maps within each species' current predicted distribution. We repeated this process for the three exposure scenarios (best-case, reference, and worst-case) across the four threats (climate change, habitat conversion, overexploitation, and fire).

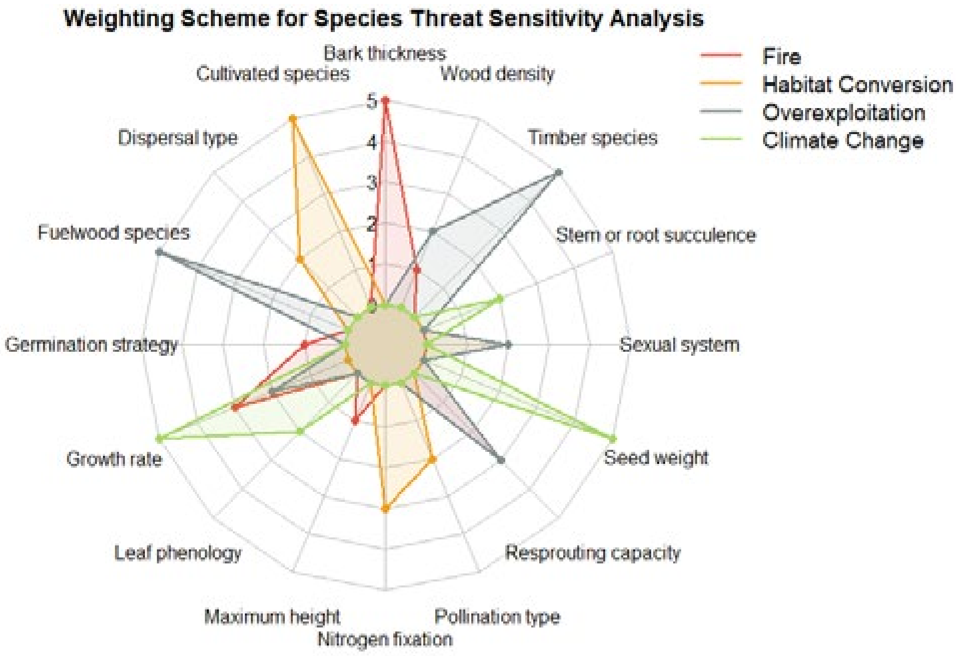

Figure 3: Threat-weighting scheme for sixteen plant traits shortlisted for determining species' vulnerabilities. The points on the radial graph represent the threat-specific weight assigned to different traits. A value of 1 is used to represent traits that are relatively unimportant to a threat (e.g. maximum height is relatively unimportant for a species' vulnerability to fire). A value of 5, on the other hand, is used to represent traits that are relatively important to a threat (e.g. bark thickness is relatively very important for a species' vulnerability to fire).

Finally, we reclassified the vulnerability maps into five areas based on the vulnerability level: zero (<0.01), low (0.01–0.25), medium (0.25–0.50), high (0.50–0.75), and very high (0.75–1.0).

We calculated the area under each vulnerability level as a proportion of the total area for each species. We also created a maximum vulnerability layer by extracting the maximum vulnerability across all threats for every pixel and assigning this vulnerability score to the corresponding pixel in the final layer. Here, too, we calculated the proportion of area under zero, low, medium, high and very high vulnerability for each species. These proportions had to be adjusted marginally due to slight spatial mismatches in the extent of our final vulnerability maps and predicted species distributions. The average error arising from these mismatches did not exceed 0.27% (± 0.22% SD) for all three scenarios combined.

Credit: Aparna Krishnan, iNaturalist

Results and Discussion

Species distribution models

Our SDMs performed reasonably well. The AUC value averaged across all species is 0.80, and the median AUC value was 0.81, indicating that the models performed well in differentiating between suitable and unsuitable habitats. Two species, *Sapindus trifoliatus* and *Syzygium caryophyllatum*, had AUC values below 0.7, indicating fair to moderate predictions. For *Sapindus trifoliatus* (AUC = 0.58 ± 0.13 SD), the poor model predictions may be attributed to its broad latitudinal range (19.23°), suggesting diverse habitat requirements that are difficult to model effectively despite having adequate occurrence data (68 records). Additionally, its moderately clustered distribution pattern and relatively high standard deviation (0.134) indicate poor predictive ability. *Syzygium caryophyllatum* (AUC = 0.69) showed the highest model variability (SD = ±0.15), likely due to its small sample size (35 occurrences), which may not provide sufficient data for robust model training. The species' highly clustered distribution suggests it may be influenced by fine-scale environmental variables or biotic factors that have not been captured in the climate data we used for modelling. However, most of the SDMs (for 28 out of 30 species) performed well with an AUC > 0.7, demonstrating the effectiveness of this approach for approximating species distributions (Table 2).

S.No.	Species	Family	IUCN status	Occurrence Records	AUC (±SD)
1	*Actinodaphne wightiana*	Lauraceae	Vulnerable	74	0.902(±0.05)
2	*Aporosa cardiosperma*	Phyllanthaceae	Vulnerable	76	0.737(±0.15)
3	*Archidendron bigeminum*	Fabaceae	Vulnerable	37	0.731(±0.13)
4	*Ardisia pauciflora*	Primulaceae	Critically Endangered	40	0.861(±0.03)
5	*Canarium strictum*	Canarium	Vulnerable	84	0.848(±0.07)
6	*Cryptocarya wightiana*	Lauraceae	Vulnerable	75	0.841(±0.14)
7	*Dimocarpus longan*	Sapindaceae	Near Threatened	128	0.864(±0.05)
8	*Diospyros candolleana*	Ebenaceae	Vulnerable	34	0.846(±0.12)
9	*Diospyros paniculata*	Ebenaceae	Vulnerable	42	0.843(±0.07)
10	*Dysoxylum malabaricum*	Meliaceae	Endangered	45	0.765(±0.14)
11	*Elaeocarpus munroii*	Elaeocarpaceae	Near Threatened	37	0.817(±0.07)
12	*Garcinia indica*	Clusiaceae	Vulnerable	83	0.794(±0.15)
13	*Hydnocarpus pentandrus*	Achariaceae	Vulnerable	54	0.772(±0.07)
14	*Litsea floribunda*	Lauraceae	Near Threatened	119	0.798(±0.06)
15	*Litsea laevigata*	Lauraceae	Vulnerable	24	0.855(±0.08)

S.No.	Species	Family	IUCN status	Occurrence Records	AUC (±SD)
16	*Litsea mysorensis*	Lauraceae	Vulnerable	23	0.895(±0.05)
17	*Litsea oleoides*	Lauraceae	Vulnerable	22	0.795(±0.08)
18	*Litsea stocksii*	Lauraceae	Vulnerable	22	0.828(±0.1)
19	*Myristica dactyloides*	Myristicaceae	Vulnerable	115	0.894(±0.03)
20	*Nothopegia beddomei*	Anacardiaceae	Endangered	73	0.838(±0.09)
21	*Prunus ceylanica*	Rosaceae	Endangered	39	0.819(±0.02)
22	*Psydrax dicoccos*	Rubiaceae	Vulnerable	77	0.808(±0.07)
23	*Pterocarpus marsupium*	Fabaceae	Near Threatened	100	0.729(±0.11)
24	*Sapindus trifoliatus*	Sapindaceae	Endangered	63	0.578(±0.13)
25	*Strobocalyx arborea*	Asteraceae	Vulnerable	39	0.781(±0.10)
26	*Syzygium caryophyllatum*	Myrtaceae	Endangered	35	0.690(±0.16)
27	*Syzygium densiflorum*	Myrtaceae	Vulnerable	20	0.861(±0.04)
28	*Terminalia paniculata*	Combretaceae	Near Threatened	76	0.738(±0.09)
29	*Vateria indica*	Dipterocarpaceae	Vulnerable	68	0.769(±0.07)
30	*Vepris bilocularis*	Rutaceae	Vulnerable	33	0.795(±0.09)

Sensitivity and Vulnerability Assessments

The proportions of species' predicted distribution ranges under the five vulnerability levels for each of the threats, along with their sensitivity to these threats, are presented in Figure 4.

On average, species were most sensitive to the threat of habitat conversion (average sensitivity = 0.89 ± 0.11 SD; Figure 4), followed by climate change (average sensitivity = 0.79 ± 0.05 SD). Sensitivity to fire and overexploitation closely followed, with average values of 0.75 (±0.09 SD) and 0.72 (±0.12 SD), respectively. The average sensitivity, across all threats and all species, was 0.79 (±0.05 SD). *Diospyros candolleana* is the most sensitive species when averaging across all four threats, followed by *Hydnocarpus pentandrus, Actinodaphne wightiana,* and *Cryptocarya wightiana* (Figure 4). On the other hand, *Ardisia pauciflora, Sapindus trifoliatus, Terminalia paniculata,* and *Pterocarpus marsupium* were least sensitive to these threats.

Habitat conversion emerged as the most important threat under the reference scenario from our vulnerability assessment. On average, 25% (± 12.6% SD) of species' predicted distributions experience high or very high vulnerability to this threat. Climate change was a close second with 21.5% (± 23.5% SD) of species' predicted distribution experiencing similar vulnerability on average. The average vulnerability to overexploitation (6.8% ± 5% SD) and fire (3.5% ± 1.8% SD) was substantially lower. These patterns remained unchanged under the best-case scenario (Figure 5a), although the vulnerability to climate change was lower on average (16.6% ± 18.2% SD), as was that of fire, albeit to a smaller extent (0.9% ± 0.6% SD). In the worst-case scenario (Figure 5b), on average, the threat that species were most vulnerable to was climate change (25.01% of distribution ± 26.2% SD), followed by habitat conversion (24.8% ± 12.1% SD), overexploitation (16.4% ± 1% SD), and fire (7.4% ± 3% SD).

When considering all threats together, 44.5% (± 18.2% SD) of species' distribution ranges, on average, faced high to very high vulnerability to at least one threat in the reference scenario. This increased to an average of 52.2% (± 17.3% SD) in the worst-case scenario. These values indicate that a significant portion of the distributions of these threatened species are highly vulnerable to at least one of the four threats considered. Other studies that have considered some of our study species have also characterised the high levels of threats that they face, particularly habitat loss and climate change (Madhavan et al., 2024; Pramanik et al., 2018; Priti et al., 2016).

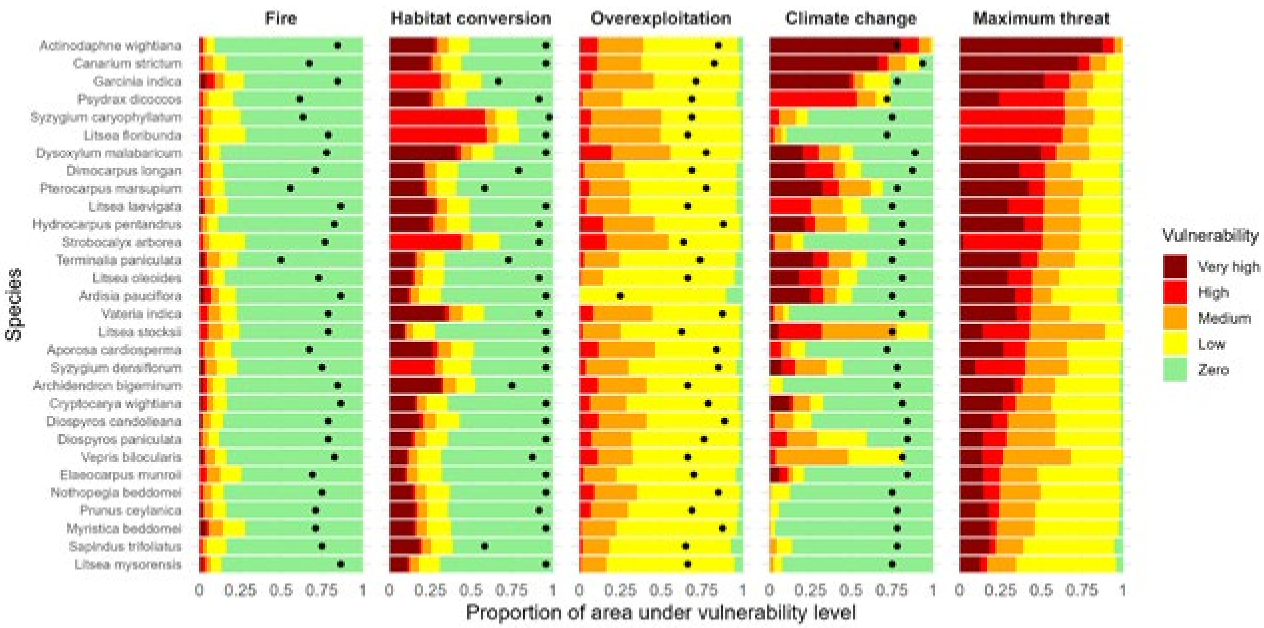

Figure 4: Summary of sensitivity and vulnerability values under the reference scenario across species distributions. The proportions of species distributions exposed to different levels of vulnerability (zero, low, medium, high and very high) to each of the selected threats are indicated by the first four columns of cumulative bar plots. The fifth column, maximum threat, indicates the highest level of vulnerability experienced by a cell of a species' predicted distribution, irrespective of the type of threat. The proportions of species distributions exposed to different levels of maximum threat are represented in this last column. The black dots in the first four columns represent species' sensitivities to the corresponding threats. The species are ranked according to the decreasing proportion of the distribution range with high or very high vulnerability to at least one of the five threats.

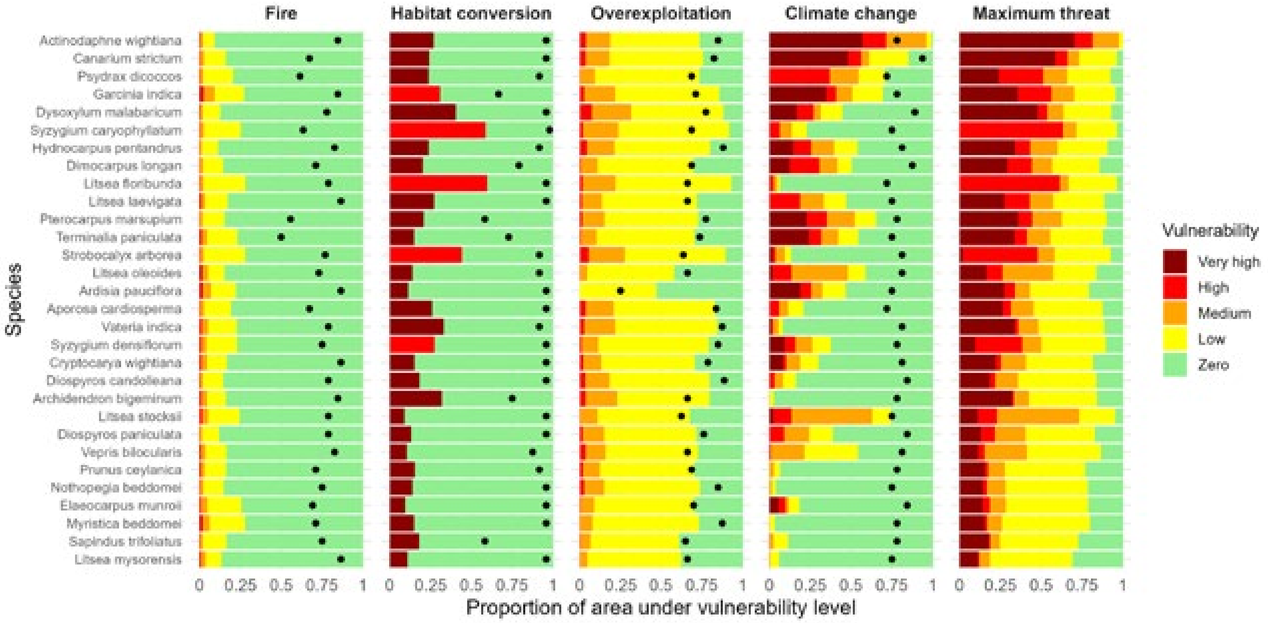

Figure 5a: Proportions of species distributions exposed to different levels of vulnerability to selected threats and maximum threat under the best-case scenario. Note that sensitivity values will remain the same across all scenarios.

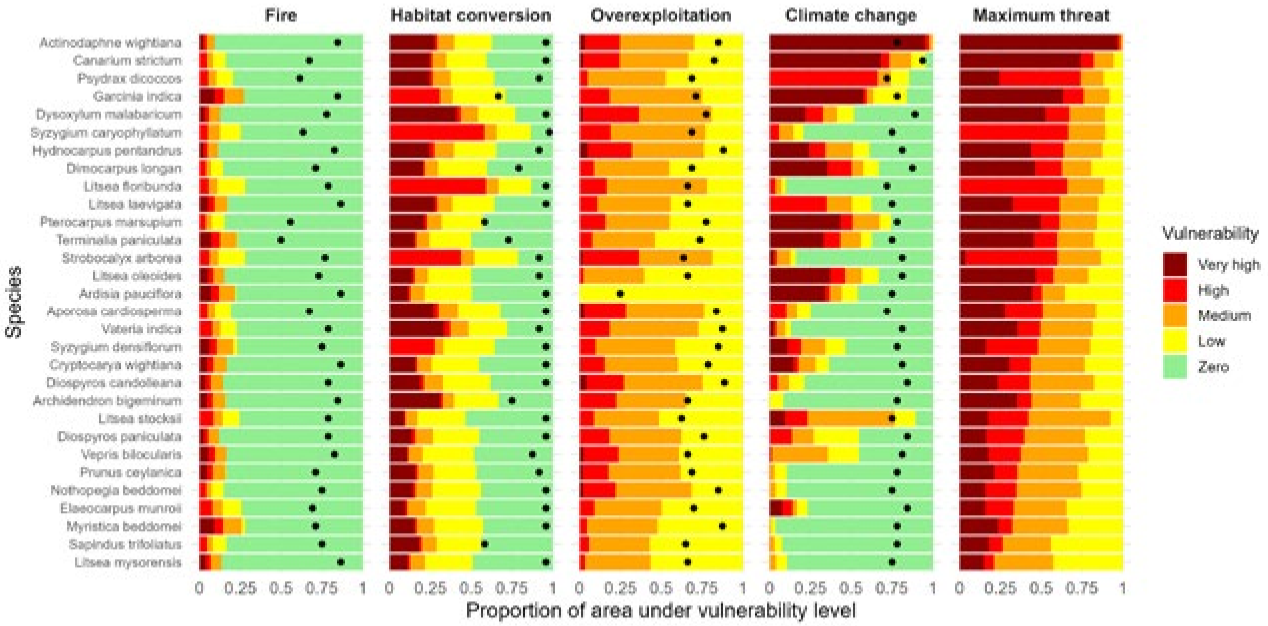

Figure 5b: Proportions of species distributions exposed to different levels of vulnerability to selected threats and maximum threat under the worst-case scenario.

Threat and Species Considerations

The high sensitivity and vulnerability of our study species to habitat conversion underscore the threat of land-use change and forest loss in the WG. The region has lost a significant portion of its natural habitat, resulting in one-fourth of all our predicted species distributions on average being vulnerable to this threat. Several studies have discussed the compounding effect of habitat fragmentation on habitat conversion, but have integrated these in their assessments infrequently. It is possible that habitat conversion is the predominant threat to our study species because we have explicitly incorporated habitat fragmentation into our reference and worst-case scenarios. However, our findings are consistent with other studies that discuss how high rates of habitat conversion in the WG impacts seed dispersal, introduces the threat of invasive species and alters environmental conditions necessary for species to establish and persist by fragmenting existing habitats (Joshi et al., 2015; Krishnadas & Stump, 2021). Worryingly, land in the WG continues to be diverted for large-scale infrastructure development projects, such as highways, power plants, and mines, even within protected areas (Gowda, 2025; Nayak et al., 2020), highlighting the importance of our observation.

Climate change is another important driver of vulnerability for our study species in the WG. Climate change is expected to increase annual rainfall in the northern latitudes of the WG and decrease rainfall in the southern latitudes. Models also indicate higher temperatures and increased rainfall seasonality, as well as frequent droughts (Katzenberger et al., 2021; Madhavan et al., 2024; Ravindranath et al., 1997). These changes are predicted to result in range expansions for some tree species and contractions for others in the Western Ghats, with some regions emerging as climate refugia for threatened species (Madhavan et al., 2024; Munoz et al., 2021; Priti et al., 2016). If future climates change at rates faster than those modelled or faster than species can adapt to the changed conditions (Ravindranath et al., 1997), the threat from climate change will be amplified.

The relatively low vulnerability of the selected tree species to overexploitation, on average, can be attributed to two reasons. Firstly, the average and median sensitivities of these threatened species to overexploitation were lower than their sensitivities to other threats (Supplementary Figure 1). Secondly, large proportions of the predicted species distributions appeared to overlap the Protected Area network in the WG region, where we had adjusted the exposure to account for the restricted resource extraction in these areas. The relatively low levels of species sensitivity and reduced exposure to threat across species distributions could have contributed to the relatively low average levels of vulnerability observed.

Interestingly, fire did not emerge as a prominent threat in all scenarios of the vulnerability assessment, which is contrary to the findings of other studies that have quantified fire as a frequent and prevalent threat to forests in the WG, especially in fragmented landscapes (Kodandapani et al., 2004, 2009). This could be attributed to reduced occurrences of fires in the predicted distribution ranges of selected species during the chosen period or/and to active fire management or prevention in parts of the region (Satish & Reddy, 2016).

Across all three scenarios— best-case, reference and worst-case—*Actinodaphne wightiana*, *Psydrax dicoccos*, *Canarium strictum*, and *Garcinia indica* emerged as the most vulnerable species (Figures 3, 4). The IUCN categorises the first two species that face the highest average vulnerabilities across their predicted distribution, as requiring ‘Least concern’ for conservation priorities (Table 2) (IUCN, 2025). The latter two highly vulnerable species are also known to be economically important. On the other hand, *Myristica beddomei, Litsea mysorensis, Nothopegia beddomei* and *Sapindus trifoliatus* were least vulnerable according to our analysis. Of these, L. *mysorensis* has been listed as ‘Vulnerable’ and N. beddomei as ‘Endangered’ in the Red-List, indicating that they are at high risk of extinction (IUCN, 2025).

This mismatch between IUCN threat categories and vulnerability assessments highlights the need to complement global listings with region-specific, multi-threat assessments to improve conservation priorities. Nevertheless, our vulnerability assessment insights highlight the need for targeted conservation and restoration efforts for these WG tree species.

Methodological Limitations

Our species-specific vulnerability assessments are dependent on and sensitive to the trait weights, trait levels and the thresholds and methods used to create the exposure maps (Fremout et al., 2020). However, the trait information is derived from expert information and the literature. Similarly, our reference threat exposure thresholds are sourced from the literature to the best possible extent or based on our knowledge of the WG. The best-case and worst-case scenarios, on the other hand, represent alternative outcomes, ranging from optimistic to pessimistic responses of species to these complex and dynamic threats. Ultimately, though, this approach has been used across tropical regions in South America (Fremout et al., 2020), Asia (Gaisberger et al., 2022) and Central Africa (Ceccarelli et al., 2022) and permits us to assess species-specific vulnerabilities for multiple threats, providing information that is crucial for species conservation.

Cross-regional Comparisons and Further Work

A cross-regional comparison of similar vulnerability assessments (i.e. Fremout et al., 2020; Gaisberger et al., 2022; Ceccarelli et al., 2022) highlights the particular risks facing WG tree species and how these patterns fit within broader tropical trends. For instance, habitat conversion affects about 25% of the current species distributions of our threatened species, even under optimistic scenarios. This is higher than the threat from habitat conversion calculated under a reference scenario in Central Africa (10%) and the dry forests of northern Peru and southern Ecuador (21%). Gaisberger et al. 2022 observed similar patterns in their study of tree species vulnerability in Southeast Asia. However, their study was conducted at a coarser scale (~4 km), and we will restrict our comparisons to the assessments from Latin America and Central Africa, which were conducted at a similar scale.

The context of each country plays a crucial role in shaping the relative vulnerability of its tree species to specific threats. Threat profiles are not uniform across tropical regions, but are closely tied to differences in economic development, land management, resource dependency, and demographic pressures. In Central Africa, smallholder agriculture and logging are the primary threats to forests, whereas large-scale habitat conversion is not as prevalent (Shapiro et al., 2023). In Latin America, large-scale agri-plantations are a significant threat (FAO and UNEP, 2020). Our work clearly illustrates the impact of habitat conversion on the vulnerability of threatened tree species. This results from the combined effects of rapid infrastructure expansion that is fragmenting habitats, agricultural encroachment that is driving habitat loss, and a dense, growing human population that compounds these patterns.

We did not choose a starting point for habitat conversion; i.e., any habitat converted from natural land use to anthropogenic land use at any point is considered to be a threat to tree species. Future work can focus on recent land-use change and explore the implications of this approach. Secondly, invasive alien species have had a dramatic impact on several WG habitats (Das et al., 2023; Muniappan & Viraktamath, 1993; Rao & Sagar, 2012); future assessments could consider including this as a threat. Finally, such assessments can be used to identify areas for conservation or restoration (e.g., Ceccarelli et al., 2022), providing valuable insights to land managers, policymakers, and other stakeholders, and should be pursued in the WG. Vitally, the abundance of high-resolution, open-access global and regional datasets has enhanced the accuracy and rigour of our vulnerability assessment. All future work must consider incorporating the best available sources so science-based insights can promote tree species conservation in the WG.

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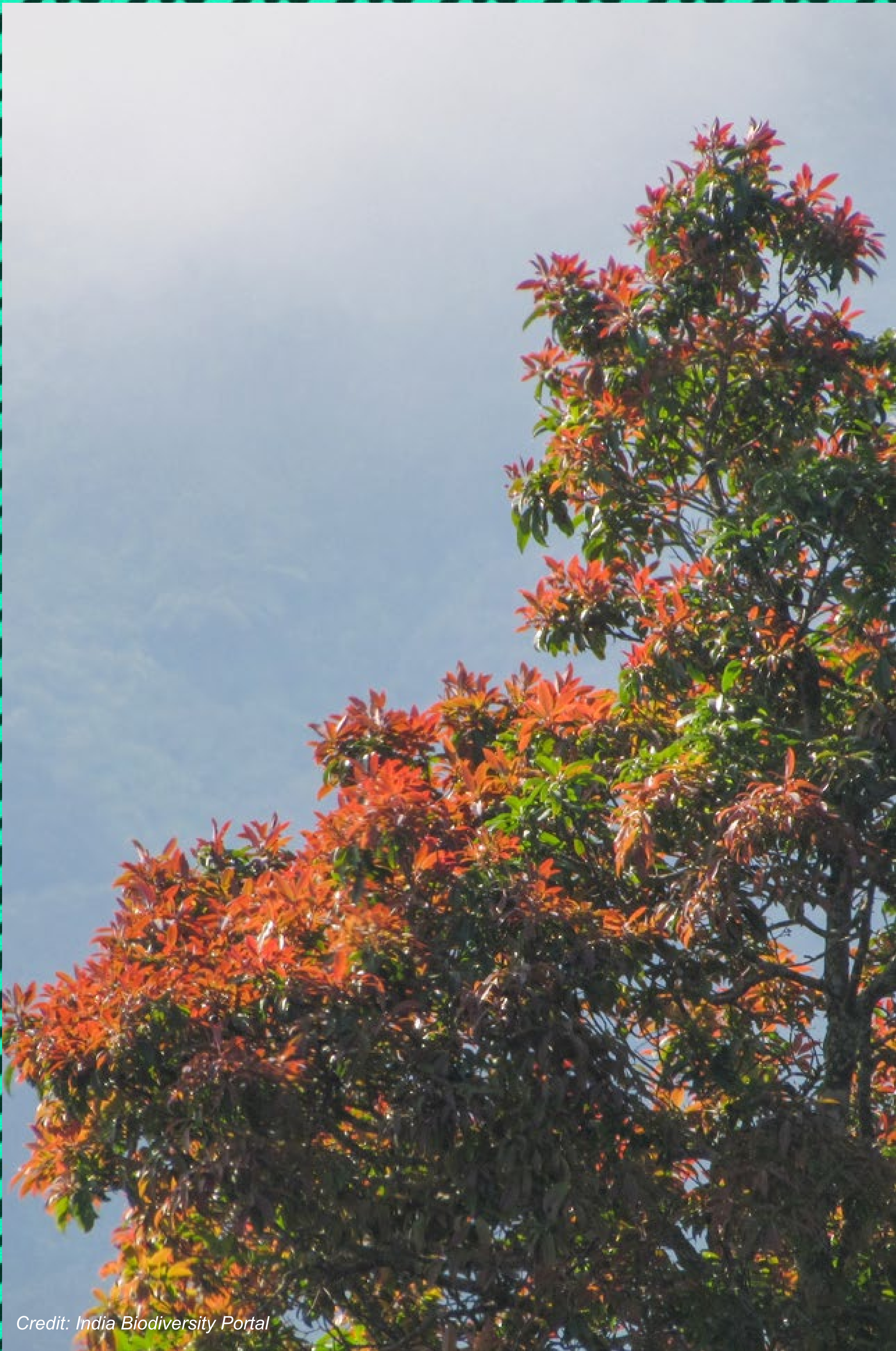
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