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Article

Distribution and Habitat Suitability of the Malabar Slender Loris (*Loris lydekkerianus malabaricus*) in the Aralam Wildlife Sanctuary, India

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Abstract: Understanding how mammals respond to climate change is critical for predicting future biogeographic shifts and implementing effective conservation strategies. In this study, we applied MaxEnt modeling to identify key determinants of the distribution of the Malabar slender loris (*Loris lydekkerianus malabaricus*), a nocturnal primate endemic to the Western Ghats of India. Using 416 slender loris sightings, spatially thinned at 0.5 km intervals to reduce spatial autocorrelation, we evaluated 19 present bioclimatic variables alongside 10 additional climatic variables. From these, 14 predictor variables with Pearson correlation values above 0.75 were selected for analysis. Future distribution models employed bioclimatic projections from the CNRM-CM5 global climate models under three Representative Concentration Pathways (RCPs): 2.6, 4.5, and 8.5. The current distribution models identified 23 km² as suitable habitat for slender lorises, with 3 km² suitable for males and 12 km² for females. Projections for 2070 under RCP 2.6, 4.5, and 8.5 scenarios predict habitat reductions of 52%, 13%, and 8%, respectively, signaling significant vulnerability under changing climatic conditions. Precipitation of the warmest quarter, precipitation of the driest month, distance from roads, and elevation were identified as the most influential variables shaping the species' distribution. This study underscores the pressing need for targeted conservation efforts to mitigate habitat loss and fragmentation, particularly in the context of climate change. By providing a detailed analysis of current and future habitat suitability, it lays the groundwork for similar predictive studies on nocturnal small mammals. As climate change accelerates, the integration of species-specific ecological insights and advanced modeling techniques will be vital in guiding conservation actions and preserving biodiversity in vulnerable ecosystems like the Western Ghats.

Keywords: nocturnal mammals; slender loris; climate change; habitat fragmentation; future climate scenario; western ghats; endemic; conservation

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1. Introduction

Climate change is a long-term global change in the earth's meteorological patterns due to natural or anthropogenic changes in surface characteristics, solar radiation, or atmospheric gas (greenhouse gas) concentrations [1]. It is one of the most important factors that disrupt structural and functional integrity of habitats [2,3]. In 2017, the International Union for Conservation of Nature's World Heritage Perspective showed that climate change was the fastest growing threat to the biodiversity of the world. Extreme environmental conditions as a result of climate change have already led to the extinction of some species and have changed their habitats and niches [4]. Bramble Cay, *Melomys rubicola* was the first mammal to be reported extinct as its habitat, coral reefs, was destroyed by rising sea levels due to the direct effects of climate change [5,6].

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Climate change also affects populations of terrestrial mammals, including primates. Climate change can lead to primate-friendly climatic conditions and habitat spatial changes; alternatively, it may fragment, shrink or expand suitable habitats [7]. For example, a study of the Sichuan snub-nosed monkey (*Rhinopithecu sroxellana*) in the Shennongjia region of China shows that the distribution range decreases with altitude, latitude, and vertical gradients, and that monkeys move to higher altitudes over time. Climate change is causing severe habitat shifts and fragmentation for orangutans [8]. Climate change can lead to range reduction or expansion depending on the habitat preferences of the species. For example, African guenons, tribe Cercopithecini, form an unusually diverse taxon. The high diversity results from relatively recent radiation, most likely due to a refugia effect around five million years ago when their ancestor's range retracted due to climate change. When their ranges expanded again, these sister species could share their habitats due to slight differences in niche preferences, leading to the species-rich guenon communities currently found in some African forests. It is therefore essential to understand how climate change will reshape the distribution of suitable primate habitats because it has implications for the management and placement of conservation areas and wildlife corridors [9].

The Western Ghats is one of the rich biodiversity regions of India. The region is also internationally recognised as a site of significant global importance for comprising areas of very high physical, aesthetic and cultural values. A large section of the Western Ghats Forest area has declined due to climate change, and the increase of agricultural land for rubber, oil palm, tea, coffee, and livestock grazing [10,11]. More specifically, increasing temperature and variability of rainfall patterns can have significant impacts on the potential distribution, and range shifts of several species as well as an overall decline in the suitable habitats in the Western Ghats [12]. Additionally, the deficit rainfall pattern of the Western Ghats may reduce the total forest cover area [13]. We have focused on a nocturnal primate species of the Western Ghats, the Malabar slender loris, to assess the effect of climate change on its habitat. Slender loris is a canopy moving small primate and any disturbance in canopy continuity can drastically impact its survival [14].

Because lorises are small and nocturnal with very small home ranges [15] understanding their distribution even at a small scale is critical for developing conservation plans for the species. Here, we aim to create current distribution maps and predict the future distribution of the Malabar Slender loris (*Loris lydekkerianus malabaricus*) using high-resolution environmental layers and occurrence data at the Aralam Wildlife Sanctuary which has the highest encounter rate of the slender loris (1.44 ±1.07 SD lorises/km) among all forest ranges in Kerala, India [16].

2. Materials and Methods

2.1. Study Site

We conducted the present study in the Aralam Wildlife Sanctuary in the south Indian state of Kerala (Figure 1). Spread over 55 km^2, the sanctuary is situated on the western slopes of the Western Ghats hills. The site lies between 11° 59’N and 11° 54’N and 75° 47’E and 75° 57’E. The elevation varies from 50m to 1145m. The vegetation consists of moist deciduous forest, semi-evergreen forest, evergreen forest, and plantations [17,18]. The temperature varies from 21°C to 40°C at foothills and 8°C to 25°C at high altitudes. The annual rainfall in the region is about 3000 mm [17,18]. A tribal settlement forms a fringe around the study site, with the Aralam Farm on one side and shared boundaries with three townships/human habitation on the other. The Valapattanam river creates a natural boundary line on the side of the township [17,18].

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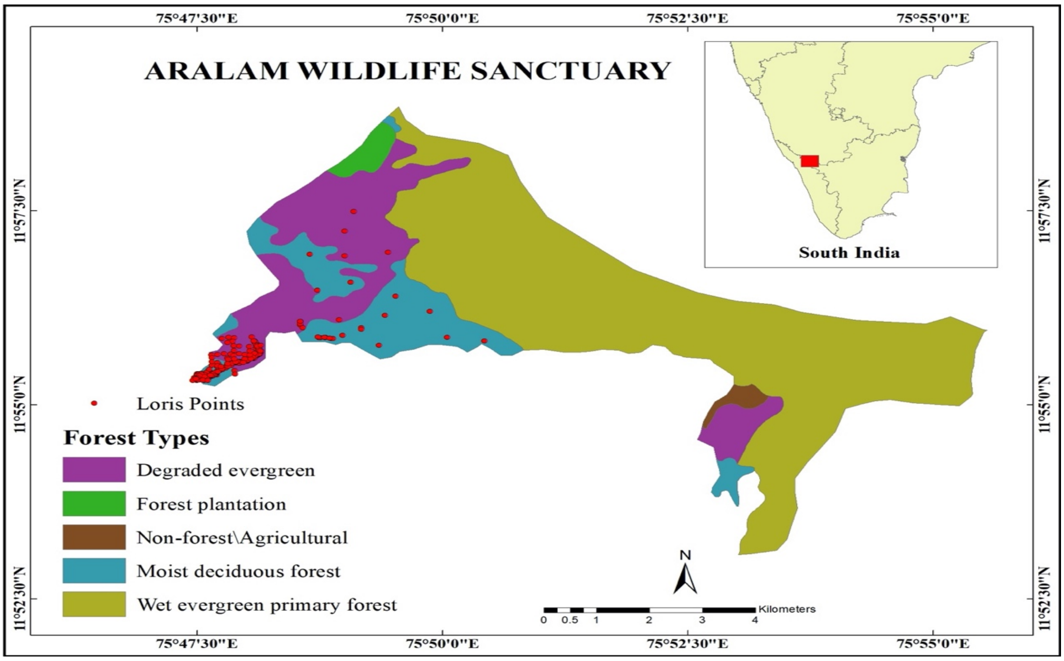

Figure 1. Map of Aralam Wildlife Sanctuary showing the points were slender lorises were detected ('loris points').

2.2. Data Collection- Loris Surveys

We conducted line transect surveys in the study area to know the occupancy and abundance of Lorises in the study area. We also incorporated occurrence data from random encounters during night surveys. A total of 416 slender loris direct sightings were taken and spatially thinned at 0.5 km (the lorises had a home range of about 1km^2) to reduce the influence of spatial autocorrelation between the occurrence points using the program Wallace [19] through RStudio version 4.0.2 (2020-06-22). We had 67 occurrence points for male lorises and 246 occurrence points for female lorises; the rest could not be identified. Spatial thinning reduced the incidence points from 416 to 33.

2.3. Habitat Suitability Modeling

We used Maxent modelling to predict the current and future potential habitats of slender loris in our study area. The maximum entropy (MaxEnt) model is a machine learning method with a flexible algorithm that creates species distribution models using presence-only species records [20,21]. The MaxEnt model is proven to better predict species habitat distribution in the various species distribution models than other predictive models [22,23]. The advantages of the MaxEnt model for target distribution modelling include firstly the integration of both continuous and categorical variables; and secondly, the output provides the least biased estimation of the target distribution [24]. Secondly, the model can deal with the risk of over-fitting by using a regularization parameter that defines the error bound around the average value of observed records and regulates the model to fit the data well [20,25]; available open-source tools such as MaxEnt software.

2.4. Downloading and Preparing Environmental Variable Layers

Changes in environmental factors such as vegetation and atmosphere make small mammal species subtle due to natural necessities and life histories [26]. Therefore, choosing influential predictors based on the ecological relevance of the species improves the accuracy of niche modeling. According to the species ecological requirements, we used 19 present bioclimatic variables downloaded from the WorldClim database at 30-sec resolution; the future climatic data, CMIP5 at 30-second resolution, was downloaded (https://www.worldclim.org/data/worldclim21.html) [27].

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The topographic layer- elevation, slope and aspect was extracted from CartoDEM Version 3-R1 layer with 2.5-second resolution downloaded from BHUVAN Indian Geo-Platform of ISRO (https://bhuvan-app3.nrsc.gov.in/data/download/index.php) using ArcGIS version 10.8 [28]. As lorises are nocturnal and sensitive to white or blue light [30], we considered night light disturbance to be an environmental variable that impacts lorises' distribution. The night-time light layer was downloaded from National Centre for Environmental Observation at 500 m (21600 x 21600 each tile) resolution (https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html). The crop use maps were downloaded from https://croplands.org/app/map?lat=0&lng=0&zoom=2. We prepared the road layer by marking the trail on a GPS device on the field; the shapefiles of the trails were loaded and processed on ArcGIS version 10.8 [28]. We downloaded the tree cover layer (Treecover2010_20N_070E.tif) from The Global Land Analysis and Discovery (GLAD) [29]. The villages layer was created by marking the borders of the villages on Google Earth Pro (7.3.3.7786) (2020 Google LLC) and then processing it using ArcGIS version 10.8 [28]. We extracted the waterbodies layer using OCM: Surface Waterlayer Products-2 day repeativity, which was downloaded from BHUVAN Indian Geo-Platform of ISRO (https://bhuvan-app3.nrsc.gov.in/data/download/index.php) using ArcGIS version 10.8 [28]. Finally, the cropland layer downloaded at 30m resolution (GFSAD30SAAFGIRCE) from NASA (https://earthdata.nasa.gov/community/community-data-system-programs/measures-projects) [31].

All predictors were rescaled to ~ 1km spatial resolution. We filtered layers after performing multicollinearity to create more consistent models and reduce the effects of highly correlated variables [32], because weakly correlated layers can compromise the accuracy of the habitat distribution model [33]. We selected 14 variables as final predictor variables from the above predictors after discarding other variables with a Pearson correlation value greater than 0.75 from the analysis.

2.5. MaxEnt Modeling for Distribution

We used MaxEnt version 3.4.1 [20] to produce a habitat distribution model of the slender loris. The technique uses categorical and continuous environmental data, and we treated all the chosen variables as continuous variables. A logistic output continuous map was selected to get the likelihood of the species present, which permits one to distinguish between the suitability of the geographical area under consideration.

The predictor environment variables were selected based on statistical correlation tests. We selected 14 layers with no correlation between the layers. We ran a test run on MaxEnt using 14 layers and estimated the relative contribution of each environment variable to the MaxEnt model. If the change in the absolute value of the lambda was negative during each iteration of the training algorithm, the adjusted gain increase was added or subtracted from the contribution of the corresponding variable to determine the initial estimate. The values of these variables regarding the presence of training and background data were randomly sorted by environment variable in the second estimate. The model was reevaluated using the sorted data, and the reductions in training AUC were normalised by percentage (Table 1).

Table 1. List of variables prepared for the MaxEnt Modelling**.**

Sl No	Variables	Description
1	Bio1	Annual mean temperature
2	Bio2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
3	Bio3	Isothermality (BIO2/BIO7) (×100)
4	Bio4	Temperature Seasonality (standard deviation ×100)
5	Bio5	Max Temperature of Warmest Month
6	Bio6	Min Temperature of Coldest Month
7	Bio7	Temperature Annual Range (BIO5-BIO6)
8	Bio8	Mean Temperature of Wettest Quarter

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9	Bio9	Mean Temperature of Driest Quarter
10	Bio10	Mean Temperature of Warmest Quarter
11	Bio11	Mean Temperature of Coldest Quarter
12	Bio12	Annual Precipitation
13	Bio13	Precipitation of Wettest Month
14	Bio14	Precipitation of Driest Month
15	Bio15	Precipitation Seasonality (Coefficient of Variation)
16	Bio16	Precipitation of Wettest Quarter
17	Bio17	Precipitation of Driest Quarter
18	Bio18	Precipitation of Warmest Quarter
19	Bio19	Precipitation of Coldest Quarter
20	ASPECT	Derived continuous layer from DEM. Calculated as compass direction of the downslope direction using spatial analyst extension of ArcGIS 10.8
21	SLOPE	Derived continuous layer from DEM. Calculated as degrees using spatial analyst extension of ArcGIS 10.8
22	ELEVATION	Digital elevation model (DEM) generated from stereo images of Indian remote sensing satellite Cartosat-1 with *30 m resolution
23	ROAD	Distance from road; derived continuous layer created by calculating Euclidean distance from road using ArcGIS 10.8
24	LANDUSE	Distance from croplands; derived continuous layer created by calculating Euclidean distance from road using ArcGIS 10.8
25	TREECOVER	Layer showing the treecover of the different forest areas
26	LIGHT	Light disturbance
27	VILLAGES	Distance from villages; derived continuous layer created by calculating Euclidean distance from villages using ArcGIS 10.8
28	WATERBODIES	Distance from waterbodies; derived continuous layer created by calculating Euclidean distance from waterbodies using ArcGIS 10.8

We adjusted the present models to the varying regularisation multipliers (1, 2 and 5) values, and the complexity of models was changed by altering MaxEnt features Linear (L), Product (P), Quadratic (Q), Hinge (H) and a combination of these features, viz., LQ, HQ, LQH, LQP, LQT, QHP, QHT, QHPT and AUTO [33]. We used the raw output format for testing the model and ran it for 5000 iterations and 30 replicates, including a subsampling procedure. We evaluated the contribution of each bioclimatic variable by using the Jack-knife protocol [22].

We used the program ENMTools 1.4.4 [20,35] to evaluate the models of varying complexities and regularisation multiplier values. We selected the model with the lowest AICc as the most suitable model depicting the present distribution of slender loris in Aralam Wildlife Sanctuary. AICc values perform better than BIC (Bayesian information criterion) or AUC (area under the curve) values for choosing best models [34,36,37]. The AUC is elucidated as the probability that the higher likelihood is assigned in a model to a presence location than an absence location, they are often not a good measure of goodness of fit and it is often observed that good, calibrated models have low AUCs and poor calibrated models have high AUCs [38]. However, AICc is a sample size corrected AIC and is suitable for model selection, especially when sample sizes are small [36,37]. The output maps were generated in ArcGIS version 10.8 and clipped onto mask layers.

2.6. Future Climatic Projections and Model Evaluations

The Representative Concentration Pathway (RCP) is a greenhouse gas concentration trajectory adopted by the IPCC Fifth Assessment Report (AR5), used four pathways for climate modeling [1], which describe different climatic futures. All these pathways are considered possible, depending on the volume of greenhouse gases (GHG) emitted in the years to come. The RCPs—originally RCP 2.6, RCP 4.5, RCP 6, and RCP 8.5— labeled after a possible range of radiative forcing values in the year

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2100 [39,40] are consistent with a wide range of possible predicted changes in future anthropogenic Green House Gas emissions and aim to represent their atmospheric concentrations [41]. The optimistic emission scenario in RCP 2.6 is likely to keep global temperature rise below 2 °C by 2100; RCP 4.5 assumes greenhouse gas (GHG) emissions peak around 2040 and then stabilizes, while in RCP 6.0, the stabilization GHG emission after 2060 and in RCP 8.5 the GHG emission will continue until 2100 [39,40].

We modelled the future climatic projections using the bioclimatic variables for simulating the representative concentration pathways RCP 2.6, RCP 4.5, and RCP 8.5 downloaded from WorldClim (https://worldclim.org/data/v1.4/cmip5.html) at 30 arc-second (~ 1 km) spatial resolution. We used CMIP5 data, which are climate projections from global climate models (GCMs) that were downscaled and calibrated (bias-corrected) using WorldClim 1.4 as the baseline climate. For long-term planning and protection of the habitat, we made projections for 2070 (average for 2061-2080). We used bioclimatic projections from the CNRM-CM5 global climate models for our future distribution models. We only considered the effect of climatic factors on the habitat suitability of slender Loris in future scenarios. Using the 10-percentile training of presence logistic threshold value from the MaxEnt output, the map showing the probability of occurrence was reclassified into 2 potential habitat categories (binary), into regions with loris and regions without loris. We created new layers of overlapping suitable habitat areas.

3. Results

The best model based on AICc scores was L1 with AUC Training and AUC Testing values of 0.71 and 0.67 respectively. The final modeled outputs show that 23 km^2 is suitable for the occupancy of lorises. The output map is shown in Figure 2.

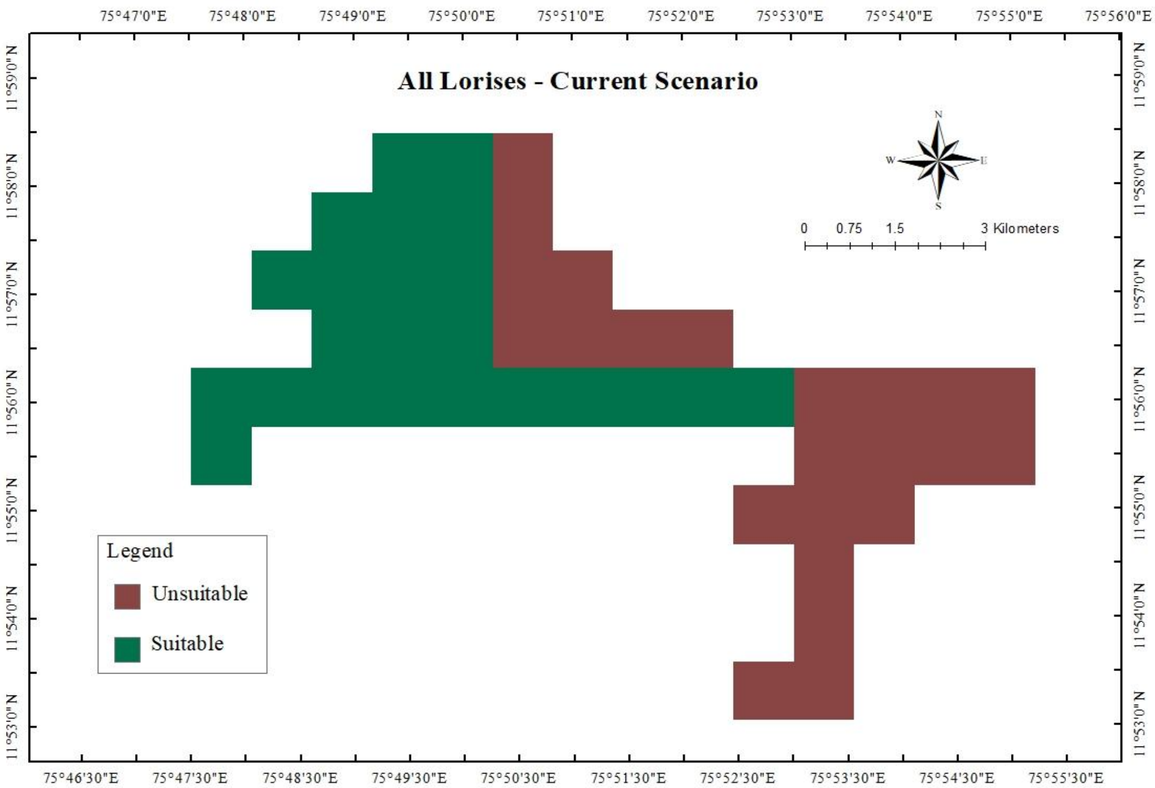

Figure 2. Habitat suitability predictions using MaxEnt for slender lorises under the current climatic conditions, vegetation and topographic features.

3.1. Important Environmental Variables

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Of the 14 variables (Table 1) used for modeling, only three showed to be affecting the spatial distribution of lorises, viz., Precipitation of Warmest Quarter (Bio 18) layer, followed by the distance from the road and Precipitation of Driest Month (Bio 14) (Table 2). The permutation importance also showed Bio 18 to have the highest importance. The result from the jackknife test for the environmental variable with the highest gain when used in isolation is Bio18, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is road, which therefore appears to have the most information that is not present in the other variables (Figure 3). The response curves from the graphs (Figure S1, S2) reflect the dependence of predicted positive suitability on the Bio 14 and Bio 18 variables, whereas it shows negative influence by road variable. The results suggest that Bio 18, Bio 14, and distance from road are the most important variables that influence the spatial distribution of lorises.

Table 2. Environmental variables used to model L1 4 and its percent contribution and permutation importance.

Variable	Description	Percent contribution	Permutation importance
Bio 18	Precipitation of Warmest Quarter	59.6	62.6
Road	Distance from road	29.4	37.4
Bio 14	Precipitation of Driest Month	10.9	0
Elevation	Digital elevation model (DEM)	0	0

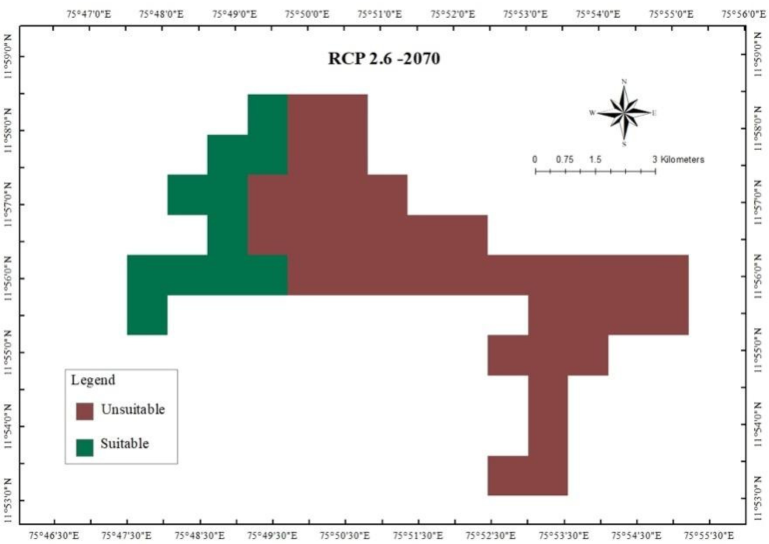
3.2. Predictions in Changes in Habitat Suitability

The percentage difference between the current and projected future distribution regions was used to assess future changes in possible species distribution. Model forecasts for the 2070s under the RCP 2.6, RCP 4.5, and RCP 8.5 scenarios found that suitable habitat areas will rapidly diminish. While comparing the three RCP scenarios, range decline in 2070 would be highest under RCP 2.6 scenario (Table 3). The map showing future predictions in RCP 2.6, RCP 4.5 and RCP 8.5 are shown in Figure 4.

Table 3. Area (km^2) showing suitable habitats under current and three future climatic scenarios.

		Suitable Habitat (in km^2)		
Habitat Suitability		**RCP 2.6**	**RCP 4.5**	**RCP 8.5**
Current Time (present)	23			
2070		11(-52.17%)	20 (-13.04%)	21(-8.69%)

a)



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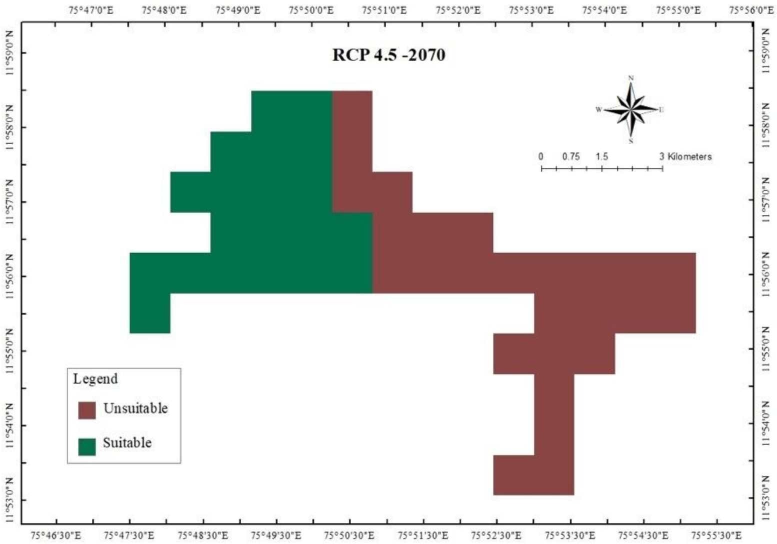
b)



c)

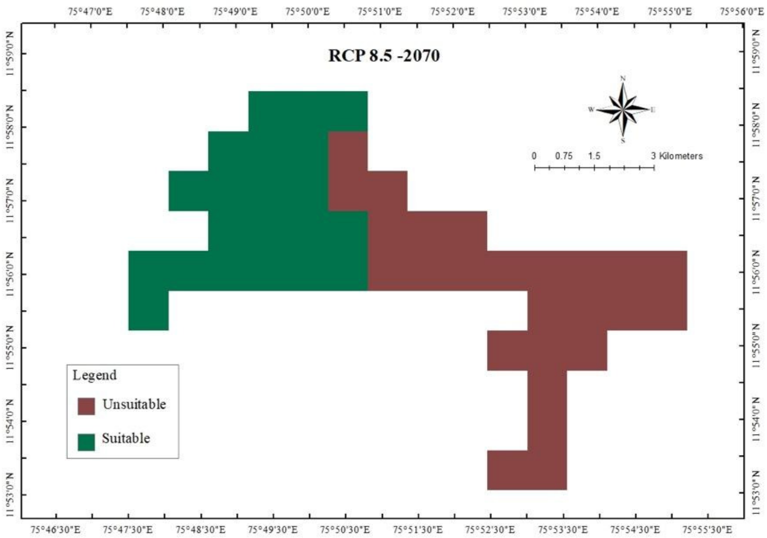


Figure 3. Predicted future potential distribution of Malabar slender loris in 2070 under climatic scenarios a) RCP 2.6, b) RCP 4.5, c) RCP 8.5.

We performed an analysis of bio18 variable in the future, by subtracting the bio18 layer from 2070 with bio18 layer of present to figure out why the most sustainable scenario showed most decline in the distribution of loris. From the figures, we can observe that the precipitation in the warmest quarter was higher in RCP 2.6 in majority of areas when compared to present precipitation, and the lorises preferred drier areas as seen in RCP 4.5 and RCP 8.5. The RCP 2.6 shows that majority of the area in Aralam show similar rainfall to wet evergreen forest in 2070 which lorises do not prefer (Figure 4), and they prefer more moist deciduous forest. Figure 1 and Figure 2 shows that lorises does not prefer evergreen rain forests.

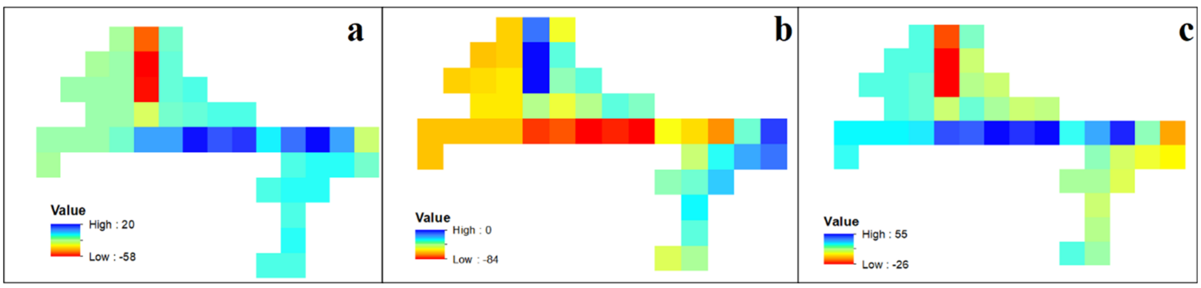


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Figure 4. The layer obtained by subtracting bio18 layer of present from bio18 layer of future a) Representative Concentration Pathway (RCP) 2.6, b) RCP 4.5 c) RCP 8.5.

4. Discussion

4.1. The Present Study and Key Findings

Predicting a species' response to changing climatic conditions on a regional and temporal scale is crucial. Generally, small-bodied mammals are indicators of climatic change and ecological system imbalance [26]. The present study represents the first attempt in India to examine how climate change impacts the Malabar slender loris (*Loris lydekkerianus malabaricus*) in a small, localized area. Our findings depict the impact of climate change on Malabar slender lorises in Aralam Wildlife Sanctuary, demonstrating that a large portion of habitat space may become unsuitable in 2070 scenario, endangering the species' viability by increasing their extinction risk.

With AUC Training and Testing scores of 0.71 and 0.67, the study identifies Precipitation of Warmest Quarter (Bio 18), distance from roads, and Precipitation of Driest Month (Bio 14) as key environmental variables influencing the species' spatial distribution. Projected habitat suitability under RCP 2.6 scenarios indicates a 52% decline by 2070, demonstrating the urgency for conservation measures [42,43].

4.2. Habitat Preferences and Variations

This preliminary study lays the foundation for expanding research across the species' entire distribution, as region-specific ecological differences in the Western Ghats could influence the variables affecting slender loris distribution. These variations align with the species' preference for moist deciduous, semi-evergreen, and degraded evergreen forests near human habitation [44,45]. Similar patterns are observed in other arboreal mammals like the lion-tailed macaque (*Macaca silenus*) and the Nilgiri langur (*Semnopithecus johnii*), which thrive in moderately disturbed habitats but are negatively impacted by urbanization and deforestation [46,47].

Our results differ from the habitat studies on *Loris tardigradus tardigradus* and *Loris l. nordicus* in Sri Lanka, wherein *Loris tardigradus tardigradus* preferred highly disturbed human habitation or highly disturbed forests [48,49], and *Loris lydekkerianus nordicus*, being a habitat specialist, was only found in undisturbed montane evergreen forests and mist forests [50] characterized with tall canopy and good connectivity.

4.3. Environmental Drivers and Anthropogenic Impacts

Precipitation of the Warmest Quarter (Bio 18) emerged as a dominant factor, aligning with findings on other species where rainfall influences habitat suitability by impacting vegetation and microhabitats [42]. Due to differences in feeding, habitat, and reproductive requirements, temperature changes may have varying effects on different species [51]. According to Kalle et al., [52], the size of a small mammal's home range determines its requirements in an ecosystem. Precipitation is one of the elements impacting the distribution of stripe necked mongooses (*Herpestes vitticollis*), according to their research from Mudumalai in the Western Ghats. Bhattacharyya et al., [53], based on observations on Royle's pika, have a similar opinion that precipitation governs the distribution. Depending on neighboring environments and the moisture requirements of certain species, local increases in precipitation may mitigate temperature-driven trends to a greater or lesser extent [54].

Proximity to roads significantly impacts various wildlife species, including slender lorises by exposing them to anthropogenic disturbances such as habitat fragmentation and increased poaching risks. Studies show that small and medium-sized mammals often exhibit reduced population densities near roadways due to these disturbances [55,56]. Additionally, slender lorises and other nocturnal mammals such as the Indian pangolin (*Manis crassicaudata*) and civets (*Viverridae*) are at heightened risk of poaching because roads facilitate easy human access to previously undisturbed habitats [57].

Primates, including slender lorises, are often found closer to roads for various reasons. Artificial lighting along roads attracts insects, providing an abundant food source [58]. Roads significantly affect primates by causing habitat fragmentation, restricting movement, and confining animals to smaller, often degraded forest patches [55]. This proximity to roads increases the visibility of species such as slender lorises, which face elevated risks of poaching and exploitation due to their association with superstitious beliefs [59]. A study in Tai National Park, Côte d'Ivoire, by N'Goran *et al*. [60] found that primate densities decreased with proximity to human infrastructure, including roads, as well as higher human and village densities. However, areas closer to research stations and tourism sites demonstrated higher monkey densities, suggesting that these zones deter poaching due to increased surveillance and law enforcement. Such findings highlight the need for targeted conservation strategies addressing both habitat protection and anti-poaching measures, particularly in regions like the Western Ghats, which host endangered species such as the slender loris.

In southern India, slender lorises are frequently targeted for use in traditional medicine and black magic rituals, where they suffer severe mutilations due to superstitions associating the species with supernatural powers [59]. This cultural belief system highlights the urgent need for community-level education and awareness programs to dispel myths surrounding the species [59].

These threats are compounded for other animals, such as pangolins, civets, and even larger mammals like leopards (*Panthera pardus*), which are poached for similar reasons in the region [61]. These findings emphasize the urgent need for region-specific conservation strategies tailored to the Western Ghats' unique ecology. Measures such as creating wildlife corridors to reconnect fragmented habitats, enforcing anti-poaching laws, and conducting community education programs to dispel harmful cultural beliefs are critical for mitigating road-related threats to these vulnerable species.

4.4. Projected Habitat Changes and Broader Implications

The projected decline in habitat under all RCP scenarios, particularly under RCP 2.6, emphasizes the interplay between precipitation, forest types, and species distribution. Increased rainfall in the warmest quarter could shift forest types from moist deciduous to wet evergreen, unsuitable for the loris [62]. This trend, compounded by habitat conversion to exotic monocultures, further threatens species reliant on native vegetation [46,47]. Conservation efforts must prioritize habitat restoration, connectivity, and community engagement to mitigate these threats.

The findings from this study have broader implications for other species in the Western Ghats, such as the Indian giant squirrel (*Ratufa indica*) and the Malabar civet (*Viverra civettina*), which face similar challenges due to climate change and habitat fragmentation [56]. Future studies must expand ecological modeling to encompass these species, enabling integrated conservation strategies across the region.

4.5. Future Directions

This study serves as a critical baseline for understanding the impacts of climate change on slender loris distribution. Future research will expand across its range to explore region-wise ecological variations and refine conservation strategies. Emphasis must be placed on elevational gradients, landscape-level planning, and species-specific interventions, including canopy bridges to improve connectivity [44]. However, such efforts must be balanced with safeguards against poaching through community awareness and involvement [64].

By combining scientific research, community engagement, and adaptive policy measures, this study provides a foundation for safeguarding the biodiversity-rich ecosystems of the Western Ghats. It underscores the need for urgent action to ensure a resilient future for both the slender loris and the broader ecological network it inhabits [65].

5. Conclusions

The Malabar slender loris (*Loris lydekkerianus malabaricus*) serves as a vital indicator species for the Western Ghats, reflecting the health of its forest ecosystems. This study highlights the species' vulnerability to climatic shifts and habitat degradation, with key environmental variables such as precipitation and anthropogenic pressures shaping its spatial distribution. The alarming reduction in habitat suitability projected under future climate scenarios, particularly RCP 2.6, underscores the need for urgent and adaptive conservation measures [66].

To ensure the survival of this unique primate, conservation strategies must prioritize habitat connectivity, such as the use of canopy bridges, while addressing the growing threats posed by deforestation, monoculture plantations, and road networks [67]. Moreover, integrating local communities in conservation initiatives through awareness campaigns and sustainable livelihood programs is essential for fostering coexistence and mitigating poaching risks [68].

The findings from this study also have broader implications for other species in the Western Ghats that share similar ecological niches and face the dual threats of climate change and habitat fragmentation, such as the Indian giant squirrel (*Ratufa indica*) and the Malabar civet (*Viverra civettina*) [69]. Future research should focus on holistic approaches, encompassing ecological modeling, landscape-level conservation planning, and region-specific mitigation strategies.

By combining scientific insights, community engagement, and policy interventions, it is possible to safeguard not only the Malabar slender loris but also the biodiversity-rich ecosystems of the Western Ghats. The preservation of these habitats is not just critical for the survival of endemic species but also for the ecological services they provide, ensuring a resilient future for both wildlife and human communities [65].

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org.

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Ethical Note: Our study was noninvasive and followed the Guidelines for Best Practices for Field Primatology of the International Primatological Society. Research protocols was approved by the Principal Chief Conservator of Forests and Chief Wildlife Warden, Forest Headquarters, Vazhuthacaud, Thiruvananthapuram- 695014 (Permit No. WL10-17697/2012) and adhered to the legal requirements to the Kerala Forest Department.

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