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Assessment of Habitat Suitability of *Carissa carandas* L. in India Using Bio-Climatic Variables, GHG Scenarios, Land Use, and Land Cover Predictors

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ABSTRACT

This study was conducted to assess the habitat suitability of *Carissa carandas* in India, which is crucial for its sustainable integration into agriculture under changing climatic conditions. We utilized Maximum Entropy (MaxEnt) modelling to evaluate the species' distribution across current and future scenarios (2050 and 2070) under four Representative Concentration Pathways (RCPs: 2.6, 4.5, 6.0, and 8.5). Results indicated that temperature-related variables, particularly the Minimum Temperature of the Coldest Month (MiTCM, contributing 46.8% in 2070 RCP 2.6) and Isothermality (contributing up to 35.2% in 2070 RCP 8.5), are the dominant climatic drivers. Land Use and Land Cover (LULC) factors such as urbanization (49.8%), total cultivated land (28.1%), and grassland (9.0%) significantly influence habitat suitability. Under the current conditions, optimal habitat spans 4,588 km², decreasing by 38.95% under LULC scenarios. Projected habitat changes indicate 2.04% gain under 2070, but 11.06% decline under 2050 RCP 2.6. Southern and western regions, including Karnataka, Tamil Nadu, Maharashtra, and Gujarat exhibit high suitability. Habitat fragmentation is projected in northern and western India due to climate change and land use modifications. These findings underscore the need for proactive conservation planning and climate-adaptive agricultural strategies to optimize the cultivation of *C. carandas*. Policymakers and stakeholders should focus on preserving suitable regions while mitigating urbanization-induced habitat loss.

Keywords Climate Change, Maximum Entropy modelling, Underutilized crop, Urbanization.

INTRODUCTION

Underutilized plant species are domesticated or wild plant species that have economic, nutritional, medicinal, or ecological value, but are not widely cultivated, traded, or researched (Ghosh *et al.,* 2023). These species are often locally important but remain underdeveloped in terms of agronomic improvements, policy support, and market integration (Padulosi *et al*., 2013). Such species have some specific traits like limited commercialization, local or indigenous importance, high resilience and adaptability, nutritional and medicinal benefits and contributing to agro-biodiversity. *Carissa carandas, Moringa oleifera, Ensete ventricosum* and *Chenopodium quinoa* are the few examples (Knez *et al.,* 2023). Further, such species could lead to innovative crop cultivation. Despite climate change, farmers can increase their income by producing these agricultural commodities sustainably (Akinola *et al*. 2020; Meena *et al*., 2022; Mugiyo *et al.,* 2022).

Despite their alleged ability to adapt to sub-optimal environments and changes in climate, there is a lack of scholarly studies focused on the consequences of climate

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change on their spatial and temporal distribution. The limited extent of policy and decision-making procedures presents a barrier to the integration of smallholder farmers into adaptation strategies (Olayinka Atoyebi *et al.,* 2017). Given the current circumstances, a cohort of esteemed researchers is advocating for the assimilation of overlooked crop varieties into agricultural and dietary frameworks in response to the ramifications of climate change (Nyathi *et al.,* 2018; Chibarabada *et al.,* 2020). Smallholder farmers integration into adaptation strategies is hindered by policy and decision-making gaps (Olayinka Atoyebi *et al*., 2017). Due to climate change, esteemed researchers are advocating for the inclusion of overlooked crop varieties in agricultural and dietary frameworks (Chibarabada *et al*., 2020).

Spatial modelling and analysis can reveal underutilized species distribution patterns (Mathur *et al*., 2023). Species Distribution Modelling (SDMs) combine species occurrence data with topographical and climatic factors to create cartographic representations of past, present, and future species distributions (Akpoti *et al*., 2020). The correlation between environmental variables and species occurrence records helps researchers understand ecological or evolutionary mechanisms and predict macroscopic agro-ecology suitability (Mathur and Mathur, 2023).

*Carissa carandas, (*Hindi= Karondais) is an Indian Apocynaceae species and commonly called "Christ's Thorn." It's an evergreen shrub (Figure 1-A) that blooms elegant white flowers from December to April (Figure 1-B). Within Indian states like Gujarat, Karnataka, and Uttar Pradesh, gardens, orchards, and small-scale plantations grow this plant for bio-fencing, live-fencing, and aesthetics (Meena *et al.,* 2022). This species can produce 5–8 kilograms of fruit in arid and semi-arid regions with little care (Figure 1-C). According to Krishna *et al*. (2017), the botanical specimen can yield 10–15 kilograms per tree when grown under proper agrarian conditions. It is used as vegetable and immature fruit is usually used in pickling and chutney. However, fully matured fruit is eaten raw or made into confectioneries and natural food colorants (Singh *et al.,* 1998). Iron-rich Karonda fruit has 39 mg/100 g vitamin C-rich fruit treats anemia and scurvy (Kanupriya *et al*., 2019). Pectin makes pickles and jellies ideal for mature fruit (Figure 1-D). These fruits can also be used to make popular preserves, drinks, and condiments.

The habitat modelling of *Carissa carandas* (karonda) is significant for various

Figure 1. *Carissa carandas* an underutilized evergreen shrub (A), utilize in landscaping for their flower (B), beautiful shiny fruits (C), and cherries are useful for preparation of pickles and vegetable (D). Presence locations of the species, use for habitat suitability modelling (E).

ecological, agricultural, and conservation-related reasons, including the followings:

(a) **Ecological importance**: *C. carandas* is a resilient, drought-tolerant shrub that flourishes in several climatic environments, and comprehending its habitat is essential for evaluating its contribution to biodiversity, particularly its relationships with pollinators and other plant species.

(b) **Agricultural and commercial significance**: The plant yields consumable fruits utilized in traditional medicine, food processing (jams, pickles), and nutraceutical sectors. Habitat modelling facilitates the identification of optimal places for its production, hence enhancing yield and profitability for farmers. It facilitates the advancement of sustainable agroforestry methods through the incorporation of *C. carandas* into agricultural systems.

(c) Conservation and sustainable utilization of its native populations are imperilled by habitat degradation, overharvesting, and alterations in land use. Modelling assists in conservation planning and in pinpointing regions suitable for protection.

(d) **Climate resilience and adaptation**: By examining its habitat preferences, researchers can assess its resilience to drought and fluctuating temperatures, rendering it a valuable species for climate adaptation strategies. Such studies can also be applied to reforestation initiatives aimed at mitigating soil erosion and desertification.

In summary, habitat modelling of *C. carandas* is essential for enhancing its agricultural utilization, preserving its natural populations, and incorporating it into climate-resilient ecosystems.

Additionally, this species' area-yield relationship, market authenticity, cost trends, and ecological studies have knowledge gaps ((Banik *et al.,* 2012; Mahajan *et al.,* 2022; Maanik *et al.,* 2023; Mishra *et al.,* 2024; Sarkar, 2024). These gaps make it difficult to understand how its distribution patterns relate to climate and land use.

Given the scientific knowledge gaps, this study investigated the habitat suitability for this species. We examined bio-climatic variables over different timescales, GHS scenarios, and land-use predictors. The Maxent model (Mathur *et al.,* 2023) was used to assess how climate change affects the spatial arrangement of arable regions suitable for Carissa carandas fruit cultivation in India. Our specific goals were to: (a) Identify the species' habitats, as delineated by current and projected climatic conditions over 2050 and 2070, within four Greenhouse Gas (GHG) scenarios, (b) Quantify the impact of diverse land utilization patterns on the species' habitat appropriateness, and (c) Identify the manifold climatic and land use factors that exert influence on both the fundamental and realized niches of this species.

MATERIAL AND METHODS

Distributional Record

Distributional records for this species were obtained from data repositories such as the Global Biodiversity Information Facility (GBIF, 2023), the Indian Biodiversity Portal (https://indiabiodiversity.org/species/show/32472), and published literature ((Singh *et al.,* 2010; CIAH 2014 and 2020; Meghwal *et al.,* 2014; Kanupriya *et al.,* 2019; Meena *et al.,* 2020) and our field work during 2005 to 2014 at various districts of arid and semi-arid areas of Rajasthan, India (Mathur and Mathur, 2023). To reduce spatial autocorrelation and eliminate duplicate records, we followed Sofaer *et al.* (2019) and used the spatial thinning window of "Wallace Software," a user-friendly graphical interface built on the R programming language (Kass *et al.,* 2018), with a thinning distance of 10 kilometres.

Bio-Climatic (Bio) and Non-Bioclimatic Variables (Non-Bio)

Machine learning helps predict species distribution based on their current range (Praveen *et al*., 2022). In this study, WorldClim version 2.0 observational bio-climatic data was used to predict species distributions (Fick and Hijmans, 2017). The study used 19 bioclimatic variables from Hijmans *et al.* (2005), extracted at a 30-second spatial resolution (~1 km^2). DIVA-GIS version 7.5 converted these variables to ASCII or ESRI ASCII (Coban *et al.,* 2020). The 2050- and 2070-time frames, which represent the mean values from 2041 to 2060 and 2061 to 2080, respectively, were used to collect data for the current and two future climatic scenarios, according to Zhang *et al.* (2021). The future datasets are associated with four Representative Concentration Pathways (RCPs): 2.6 W/m^2 (lowest emission), 4.5, 6.0, and 8.5 W/m^2 (highest emission, Chaturvedi *et al.,* 2012). Table 1 summarizes bio-climatic parameters, including units and mathematical expressions.

Land Use and Land Cover (LULC)

Various Land Use and Land Cover (LULC) predictors, including rain-fed and irrigated land, total cultivated land, forest, Grass/Scrub/Woodland (GRS), barren/very sparsely vegetated land (NVG), urban land, land used for housing and infrastructure, and wet lands, have been employed to forecast the suitability of habitats for this particular species. These variables were downloaded from web at a resolution of ~1 km^2 utilized as recommended by Fischer *et al.* (2008)

Issue of Multicollinearity

The Pearson correlation coefficient (r) was used to examine cross-correlation, and multicollinearity was examined to assess over-fitting. We also followed Pradhan *et al.* (2016) to eliminate variables with cross correlation coefficients of 0.85 or higher. This was accomplished through the utilization of the Niche Tool Box, as described by Osorio-Olvera *et al.* (2020a, b). A singular variable, which exhibits substantial cross-correlation and holds biological relevance to the species, was selected from a set of two alternative variables for the purpose of simplifying model

Table 1. Description of predictive bio-climatic variables use in this study.

Code	Environmental variables and their abbreviations	Scaling	Unit
Bio -1	Annual Mean Temperature (AMT)	10	°C
Bio -2	Mean Diurnal Range (MeDR)	10	°C
Bio -3	Isothermality (Bio 2/Bio 7) (×100) (Iso)	100	-
Bio -4	Temperature Seasonality (Standard deviation×100) (TempS)	100	-
Bio -5	Max Temperature of Warmest Month (MaTWaM)	10	°C
Bio -6	Min Temperature of Coldest Month (MiTCM)	10	°C
Bio -7	Temperature Annual Range (Bio 5- Bio 6) (TAR)	10	°C
Bio -8	Mean Temperature of Wettest Quarter (MeTWeQ)	10	°C
Bio -9	Mean Temperature of Driest Quarter (MeTDQ)	10	°C
Bio -10	Mean Temperature of Warmest Quarter (MeTWaQ)	10	°C
Bio -11	Mean Temperature of Coldest Quarter (MeTCQ)	10	°C
Bio -12	Annual Precipitation (AnPr)	1	mm
Bio -13	Precipitation of Wettest Month (PrWeM)	1	mm
Bio -14	Precipitation of Driest Month (PrDM)	100	mm
Bio -15	Precipitation Seasonality (Coefficient of Variation) (PrS)	1	Fraction
Bio -16	Precipitation of Wettest Quarter (PrWeQ)	1	mm
Bio -17	Precipitation of Driest Quarter (PrDQ)	1	mm
Bio -18	Precipitation of Warmest Quarter (PrWaQ)	1	mm
Bio -19	Precipitation of Coldest Quarter (PrCQ)	1	mm

interpretation (Mathur and Mathur 2023).

Projection Transformation

The Bio-Climatic (Bio) and Non-Bio variables were obtained from different sources at different resolutions, so, they were standardized before extracting data and generating predictions using machine learning tools. We used ArcMap and ArcToolbox to follow a methodology for analysis. The Data Management Tools interface's "projection and transformation" section explained the projection (Jijon *et al.,* 2021). To quantify area under each habitat suitability class in Arc Map's "calculate geometry" window, we converted the habitat class raster file projections to WGS 1984 web Mercator (auxiliary sphere-3857).

Species Distribution Modelling

The present study used Maxent 3.4.1 (http://www.cs.princeton.edu/schapire/Maxent/) to simulate and predict *C. carandas* plausible geographic distribution likelihood using the current scenario, two future scenarios (2050- and 2070-time frames), and a non-climatic variable. This tool's discrete execution with each predictor in isolation allowed us to accurately measure their impact on the species' distributional pattern. Background points were randomly generated at 10,000 (Zhang *et al.,* 2021). We set the regularization multiplier to 0.1 to avoid test data overfitting. (Phillips *et al*., 2006), while the rest were left at their software defaults. To calibrate and validate Maxent model evaluation, threshold-independent Receiver-Operating Characteristic (ROC) analyses were used, and an Area Under the receiver operating Curve (AUC) was used to estimate model predictions (Elith *et al.,* 2006). Based on the AUC value, the model was classified using the conservative guide suggested by Thuiller *et al.* (2005) and Kagnew *et al.* (2023) as: failing (0.5-0.6), poor (0.6-0.7), fair (0.7-0.8), good (0.8-0.9), or excellent (0.9-1). The model performs well with AUC values near one (Mathur *et al.,* 2023).

Variable Importance values and response curves were used to assess how bioclimatic and non-bioclimatic variables affected this species' distribution (Mathur and Mathur, 2023). We then used ArcGIS to convert the Maxent output ASCII file into raster format and classified (Ali *et al.,* 2023) this species' habitat with help of "Raster Calculation Tool" into areas as optimal (1.0 to 0.80), moderate (0.80 to 0.60), marginal (0.60 to 0.40), low (0.40 and 0.20), and absent (< 0.20). Then, the optimum habitat raster file was converted into Keyhole Markup Language (KML) to accurately identify ideal habitat changes across diverse climatic temporal intervals and LULC compared to the current optimal habitats. Percent changes (gain and loss) in areas of optimum habitat suitability under different climatic and non-climatic variables in comparison to current optimum area were calculated using the following formula provided by (Mathur and Mathur, 2023). This exercise allowed us to quantify optimal habitats based on climatic time frames, RCPs, and LULC.

$$\left(\frac{Future\ Optimum\ Area - Current\ Optimum\ Area}{Current\ Optimum\ Area}\right) x100$$

Ellipsoid Niche Hypervolume

Machine learning models offer a variety of significant variables to enhance the precision of species localization. The quantification of hypervolumes linked to the niches of this particular species was carried out by employing the top three predictors across all bioclimatic scenarios and RCPs, in addition to LULC variables. In the present study, we utilized NicheToolBox (Osorio-Olvera *et al*., 2020a) software program coded in the R programming language, necessitates the invocation of the raster output pertaining to BC variables. Ellipsoidal models were constructed through the calculation of the centroid and covariance matrix of the environmental values of the species. The research region was comprehensively examined, with all potential settings radiating outward from its geographic epicentre. Through the utilization of this particular methodology, we were able to determine the environmental factors that dictate the fundamental and realized niche of the said species.

RESULTS

Multicollinearity and Model Performance

By conducting an extensive examination of a wide array of sources (as mentioned in material and method) originating from the Indian region, we effectively derived a total of 285 locations where this particular species can be found. Using Wallace Software's spatial thin window feature (Kass *et al.,* 2018), we eliminated all instances of a record within a 10-kilometer radius. Integrating 218 *C. carandas* presence points without spatial autocorrelation completed the ENM development process (Figure 1-E). The final bioclimatic variables and their percentage contributions are shown in Table 2, which uses the "x" symbol to exclude variables from their bioclimatic time frame and RCPs. Based on their strong correlations with bioclimatic factors, Bio-1,2, 9,10,11,12,14,15, and 18 were excluded from future analyses. Figures 2-a (current) and -b (LULC) show model quality results in terms of AUC. Additionally, Figures 2-c to -f show the 2050 climatic time frame results for each Representative Concentration Pathway (RCP). Figures 3-a to -d show the 2070 results and RCPs. Since all AUC curves exceeded 0.80, model performance was good.

Percent Contribution of Bio-climatic and LULC Variables

Table 2 and Figure 4 show bio-climatic and LULC variable percentage contributions. The Minimum Temperature of Coldest Month (Bio-6 MiTCM) is the primary bio-climatic predictor that significantly affects this species' habitat suitability across various climatic time-frames and RCPs, except for 2070 RCPs 6.0 and 8.5. In these situations, isothermality (Bio-3), the ratio between the annual mean temperature and the mean diurnal range, controls the species the most. This climatic variable is the second most influential factor in all future Representative Concentration Pathways. However, given the bioclimatic conditions, temperature seasonality (Bio-4) is the second most important factor affecting this species' habitat suitability. Temperature Annual Range (Bio-7 TAR) and Mean Temperature of the Wettest Quarter (Bio-8 MeTWeQ) are the least effective bio-climatic factors. In Land Use and Land Cover (LULC) variables, urbanization, cultivated land, and grassland are influential.

Table 2. Maxent output showing percent contribution of the different bioclimatic variables to the model with respect to bioclimatic time-frames and their RCPs.

Bio		2050 RCPs				2070 RCPs			
Variables	Current	2.6	4.5	6.0	8.5	2.6	4.5	6.0	8.5
Bio-3	x	28.3	27.4	25.9	33	25	28.7	34.6	35.2
Bio-4	29.2	3.7	3.3	5.2	1.1	2.6	3.1	4.3	4
Bio-5	x	14.7	x	x	9	8.7	9.8	18.5	10.2
Bio-6	36.9	33.3	42.1	38.9	35.6	46.8	36.5	0.7	28.3
Bio-7	0.9	x	2.1	3.5	0.6	3.6	3.9	1.1	0.1
Bio-8	4.7	1.3	7.9	5.1	3	3.8	1	10.4	4.8
Bio-13	12.9	6.7	6.8	10.7	11.5	5.3	3.4	13.2	5.4
Bio-16	5.3	6.4	5.9	6.3	6.2	4.2	7.5	10.8	9
Bio-17	7.3	5.7	x	x	x	x	x	x	x
Bio-19	2.8	x	4.5	4.4	x	x	6.1	6.5	3

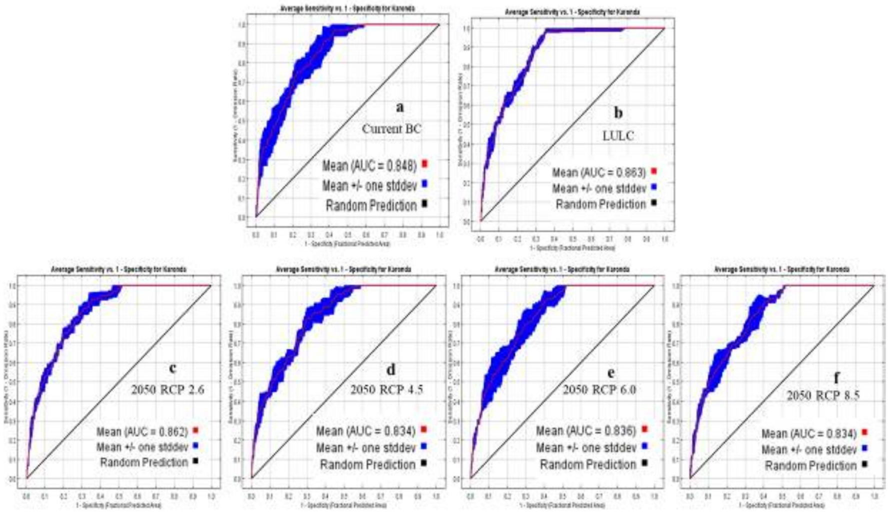

Figure 2. The area under the receiver operating curve with current bio-climatic (a), LULC (b), future climatic time frame (2050) with four RCPs namely 2.6 (c), 4.5 (d), 6.0 (e), and 8.5 (f).

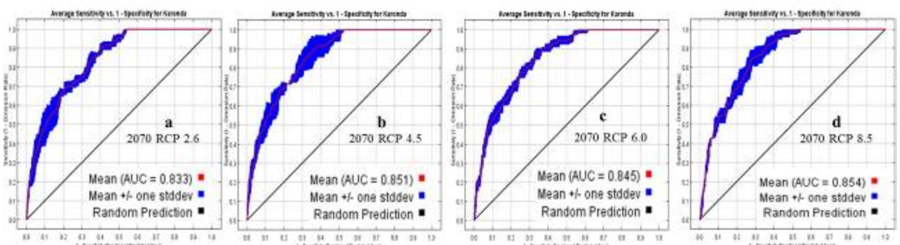

Figure 3. The AUC curve with future climatic time frame (2070) with four RCPs namely 2.6 (a), 4.5 (b), 6.0 (c), and 8.5 (d).

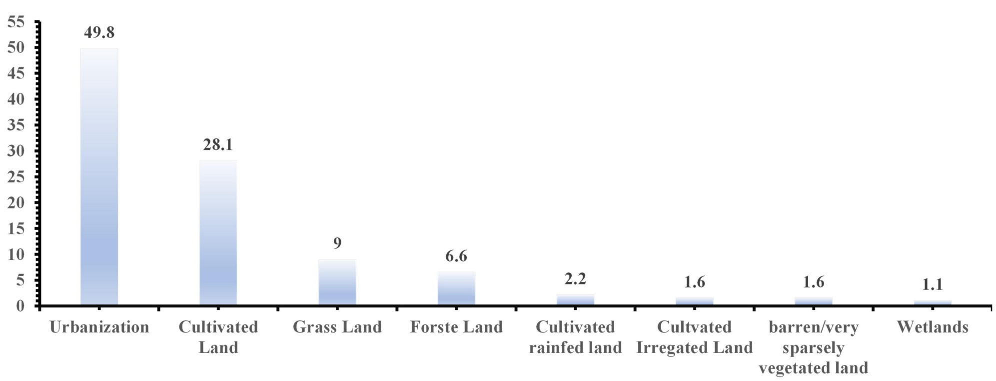

Figure 4. Variable importance values of Maxent output with different variables of LULC.

Their percentage contributions are 49.8, 28.1, and 9. Cultivated rain-fed and irrigated land, barren land, and wetlands have variable importance values below 2.0.

The supplementary material (Figures 1–10) shows response curves for the three most important bio-climatic and land use/land cover variables. The response curves showed that the projected species suitability values with MiTCM variables were highest at 15°C for both present conditions and all future Representative Concentration Pathways (RCPs), except 6.0 and 8.5 in 2070. Isothermaility has had the greatest impact on these two RCPs. Additionally, species suitability peaked at 50 and ranged from 40 to 55. Temperature seasonality peaks between 20 and 40°C. Urbanization and grassland have skewed curves in LULC variables. Urbanization peaks between 10 and 20, while grassland peaks between 5 and 10. Cultivated lands have a wider spectrum, peaking at 35 to 60.

Habitat Suitability Areas (km^2)

Table 3 shows habitat suitability areas for optimal, moderate, marginal, and low habitat types. The spatial distribution of these areas is shown in Figure 5-a for the current climatic time, and in Figures 5-b to -e for 2050 and its RCPs. Figures 6-a to -d show 2070 habitat suitability and RCPs. Lastly, Figure 7 shows LULC patterns for each habitat type: optimum (Figure 7-a), moderate (Figure 7-b), marginal (Figure 7-c), and low (Figure 7-d). In the optimal class, 2070RCP 2.6 had the largest land area (46.82×10^2 km^2). In 2050 RCP 2.6, the bio-climatic variables had the smallest area (40.81×10^2 km^2), followed by 2070 RCP 8.5. The optimal habitat type covers 45.88×10^2 km^2 under current climate conditions. The LULC optimum suitability habitats (km^2) had the smallest area, 28.01×10^2 km^2. The areas with the greatest extent were moderate (70.85×10^2 km^2) and low (16.19×10^3 km^2), under the current bioclimatic conditions. Conversely, 2070 RCP 4.5 (34.51×10^2) and land use and land cover change (50.08×10^2) had the smallest areas for above classes. LULC had the highest marginal class area (15.04×10^3).

Based on analysis of habitat suitability classes and their spatial extents, this study proposes the existence of optimal regions in the southern (Karnataka and Tamil Nadu), as well as in the western (covering the western Ghat region of Maharashtra and Goa, and some scattered areas in Gujarat) areas of India, which exhibit similar characteristics across various bio-climatic time frames and RCPs. Nonetheless, LULC predictors have shown fragmented patterns in optimum habitat. Furthermore, this habitat has been observed in both the eastern (Odisha, Jharkhand, West Bengal) and northern (Uttar Pradesh, New Delhi, Uttarakhand) parts of the country. Furthermore, given the current climatic conditions, it is found that specific regions in the west (Gujarat, Rajasthan), north (Uttar Pradesh), and south (Andhra Pradesh) are moderately favourable for this species. Given the steady evolution of climatic conditions projected for 2050, as well as the four RCPs, it is expected that certain portions of western India, particularly Maharashtra, will see the emergence of suitable habitats for this species. However, it is vital to highlight that habitat fragmentation is likely to occur in the country's northern territories, including Uttar Pradesh, as well as western portions (Gujarat and Rajasthan), resulting in the split and isolation of these ecosystems. The moderate portions of Gujarat (western part of the country) will either become a marginal habitat by 2070 (RCP 2.6) or proceed to an optimum habitat under RCP 4.5, 6.0, and 8.5 scenarios. The central areas of India are distinguished by the presence of habitats with marginal or low ecological value. In addition to optimum habitat, we have documented fragmented and patchy habitats classified as moderate, marginal, or low with LULC. This species cannot be grown in the extreme western region (Rajasthan), which has a hot and arid climate and encompasses Barmer and Jaisalmer districts. Similarly, the northern region, such as Jammu and Kashmir, as well as Ladakh, are unsuited for cultivation of this species. Finally, the eastern areas of the country, notably Arunachal Pradesh and Sikkim, do not have ideal circumstances for cultivating this plant.

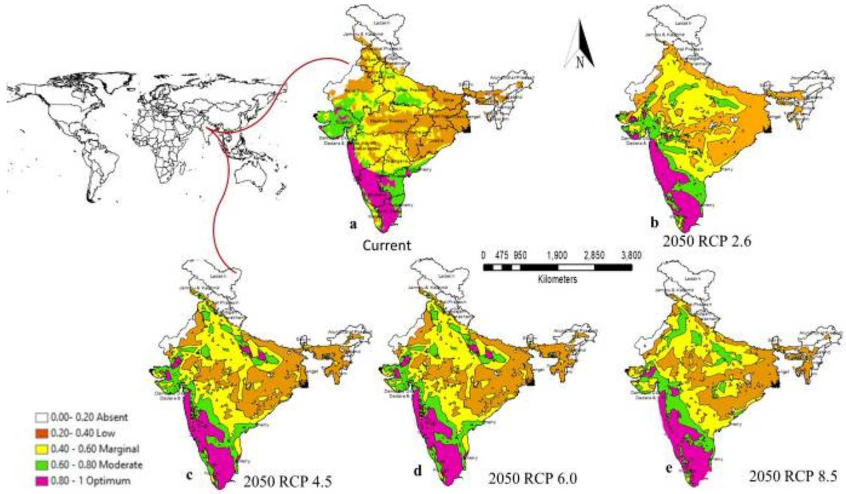

Figure 5. Habitat suitability of *C. carandas* under different classes with current (a) and 2050 bio-climatic time frame with its four RCP 2.6 (b), RCP 4.5 (c), RCP 6.0 (d), and RCP 8.5 (f).

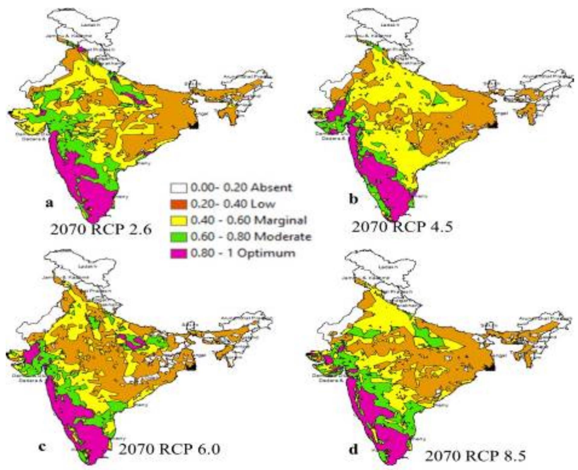

Figure 6. Habitat suitability of *C. carandas* under different classes with 2070 bio-climatic time frame with its four RCP 2.6 (b), RCP 4.5 (c), RCP 6.0 (d), and RCP 8.5 (f).

Spatial Changes in Optimum Habitats

As evaluated using various predictors, Figure 8 shows the percentage changes in the most suitable habitat's extent relative to the optimal area. The spatial distribution of these alterations is shown in Figure 9-a to -e (current+2050, along with their RCPs) and Figures 10-a to -d (current+2070 RCPs) for two future climatic-time frames. Based on LULC parameters, this suitability class is highly fragmented. Comparatively, this fragmentation has decreased by 38.95%. This species has a marginal gain of +2.04 for 2070 under the RCP 2.6 scenario and +1.06 under the RCP 4.5 scenario. With the previous one, hilly regions of norther India (Himachal Pradesh, Uttarakhand, Uttar Pradesh), western parts (covering areas adjoining to Ahmedabad, Morbi, Rapar, Bhabhar, Tharad, Dhanera, Deesa, Raniwara Gir National Park in Gujarat, and Bhinmal Gudamalani in Rajasthan) had the highest gain of 2070RCP4.5. However, optimal habitats decreased by -11.06 and -8.75% under the 2050 and 2070 RCPs 2.6 and 8.5, respectively. RCP 4.5, 6.0, and 8.5 of 2050 showed less than 5% loss in optimum habitats (Figure 8).

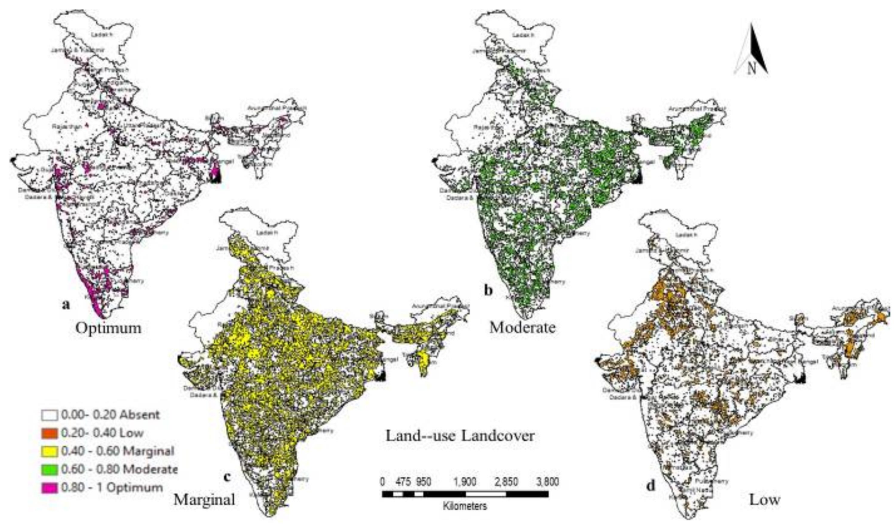

Figure 7. Habitat suitability of *C. carandas* under different classes with LULC: Optimum (a), moderate (b), marginal (c), and low (d).

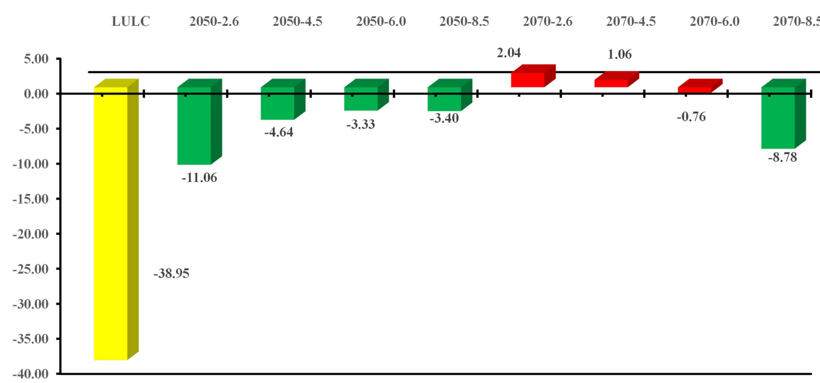

Figure 8. Percent changes (gain and loss) in areas of optimum habitat suitability under different climatic and non-climatic variables in comparison to the current optimum area.

Table 3. Area (km^2) of different habitat suitability classes with studied predictors.

Variables	Optimum	Moderate	Marginal	Low
Current	45.88×10^2	70.85×10^2	12.78×10^3	16.19×10^3
Land use and Landcover	28.01×10^2	53.93×10^2	15.04×10^3	50.08×10^2
2050RCP2.6	40.81×10^2	48.10×10^2	11.49×10^3	10.77×10^3
2050RCP4.5	43.75×10^2	54.09×10^2	11.43×10^3	10.96×10^3
2050RCP6.0	44.35×10^2	50.59×10^2	10.97×10^3	11.75×10^3
2050RCP8.5	44.32×10^2	53.97×10^2	11.42×10^3	10.38×10^3
2070RCP2.6	46.82×10^2	60.92×10^2	10.50×10^3	10.65×10^3
2070RCP4.5	46.37×10^2	34.51×10^2	13.16×10^3	10.21×10^3
2070RCP6.0	45.53×10^2	46.85×10^2	85.74×10^2	11.76×10^3
2070RCP8.5	41.85×10^2	54.29×10^2	92.05×10^2	12.36×10^3

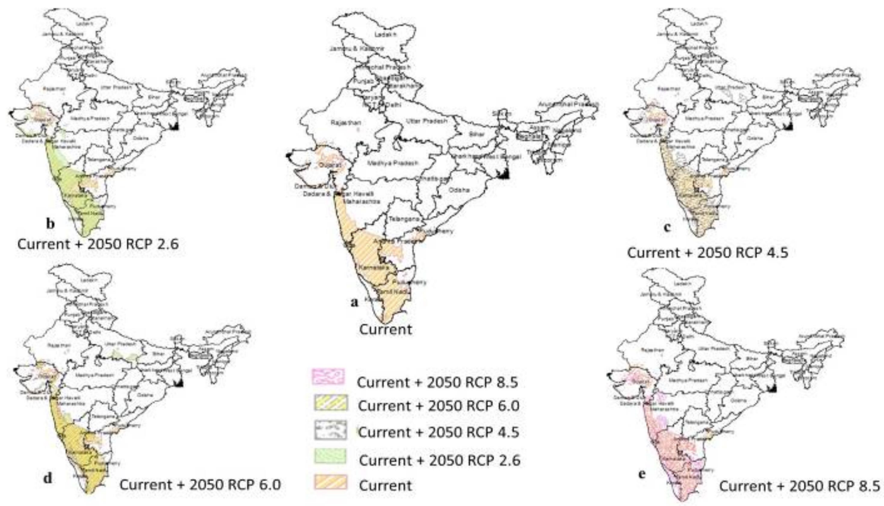

Figure 9. Superimposition of the current optimum suitability sites (a) with different RCPs of 2050 2.6 (b), 4.5 (c), 6.0 (d), and 8.5 (e).

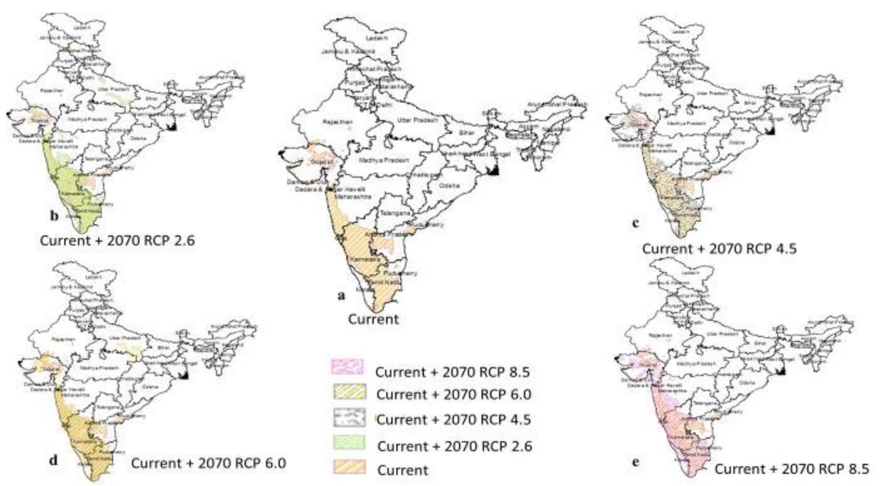

Figure 10. Superimposition of current optimum suitability sites (a) with different RCPs of 2070 2.6 (b), 4.5 (c), 6.0 (d), and 8.5 (e).

Ellipsoid Niche Hypervolume

Using the existing dataset, we constructed an ellipsoid hypervolume, which represents a multidimensional space encompassing the available resources for a given species. This hypervolume was employed to simulate both the fundamental niche, which refers to the species' capacity to persist and reproduce in a wider range of environments in the absence of interspecific competition, and the realized niche, which considers the species' interactions with other coexisting species. To achieve this, we utilized projected occurrence records of the species *C. carandas*, along with the pertinent environmental variables that were identified as crucial through the Maxent algorithm, presented in the form of raster output. This enables us to discern the variables that dictate both its fundamental and realized niche. The results are display in Figures 11-a (current bio-climatic) and -b (LULC), 12 (a-d) (2050 and its RCPS) and 13 (a-d) (2070 and its RCPS). Within these visual representations, the utilization of the blue hue signifies the concept of niche stability, while the incorporation of the color green conveys the notion of niche unfilling, denoting the extent to which the native niche remains unoccupied by the exotic niche. Additionally, the inclusion of the red hue serves to symbolize the phenomenon of niche expansion (Mathur and Mathur, 2023). The dimensions of these zones are directly proportional to the magnitude of their respective ecological niche. In terms of bioclimatic space, *C. carandas* ellipsoidal niche had a larger hypervolume (82.21×10^{3}°C mm^{2}) with the current bio-climatic conditions, followed by 2.6 RCPs of 2050 (60.24×10^{3}°C mm^{2}) and 2070 (57.16×10^{3}°C mm^{2}), and among the bioclimatic variables it was the smallest (23.06×10^{2}°C mm^{2}) during the 2050 RCP 4.5. However, with LULC, it was recorded minimum having 19.26×10^{2}°C mm^{2}. The manifestation of environmental factors on the dynamics of ecological niches is denoted by the centroid values associated with these variables. The spatial proximity of these entities to the centroid serves as a reliable indicator of their capacity to exert influence over the suitability of species (Nunez-Penichet *et al.,* 2021). The values pertaining to the centroid of various bio-climatic

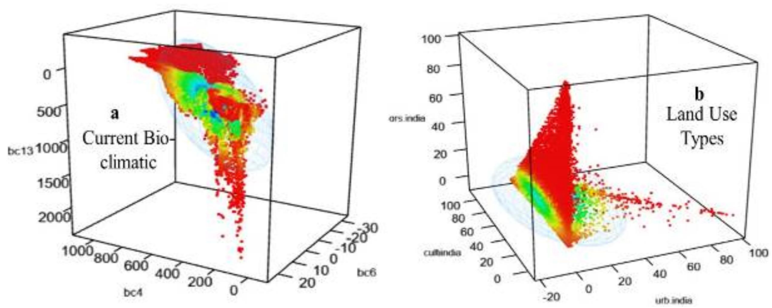

Figure 11. Graphical representation of *C. carandas* niche hypervolume with three most influential variables pertains to the current bioclimatic (a) and LULC (b) predictors.

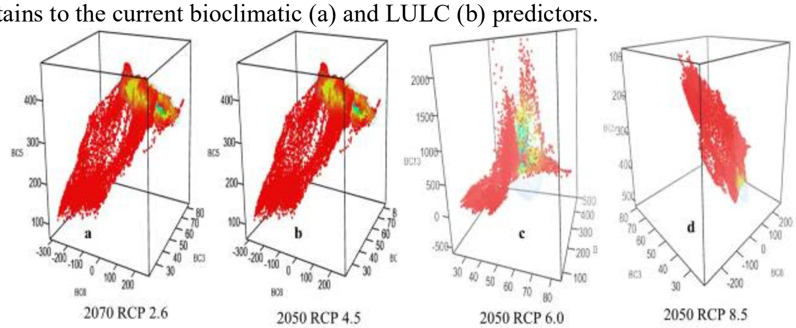

Figure 12. Graphical representation of *C. carandas* niche hypervolume with three most influential variables pertains to 2050 bioclimatic time frame with its four RCPS namely 2.6 (a) 4.5 (b), 6.0 (c) and 8.5 (d).

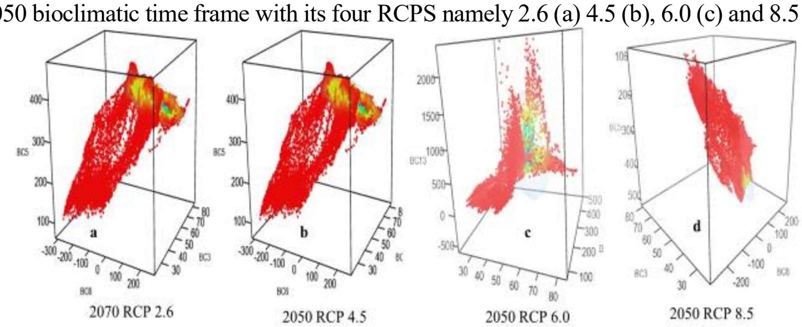

Figure 13. Graphical representation of *C. carandas* niche hypervolume with three most influential variables pertains to 2070 bioclimatic time frame with its four RCPS namely 2.6 (a) 4.5 (b), 6.0 (c) and 8.5 (d).

variables across three distinct time frames are displayed in Table 4.

This species expands its ecological niche mostly beyond its fundamental niche in relation to precipitation levels during the wettest month (Bio-13, the water variable) in the current climate. Table 4 also shows that temperature seasonality (Bio-4) and the minimum temperature during the coldest month (Bio-6) help preserve these niche areas. This analysis of all four RCPs from 2070 shows that the warmest month's maximum temperature (Bio-5) controls the expansion of its fundamental niche. Alternatively, isothermality, the minimum temperature of the coldest month, and the precipitation of the wettest month (2070 RCP 6.0) support these niche areas. Except for RCP 4.5 in 2050, the other RCPs suggest that, like the current situation, its niche expansion is primarily influenced by precipitation levels during the wettest month. In RCP 4.5, the mean temperature of the wettest quarter (Bio-5) dominates this expansion. The centroid value of 52.93 for the LULC variables indicates that cultivated lands control C. carandas' fundamental niche expansion. Urbanization (13.29) and barren/sparsely vegetative areas (5.47) help this species maintain its niche.

DISCUSSION

The Asian continent persists in grappling with a significant incidence of malnutrition. The enduring state of malnutrition can be ascribed to a deficiency in dietary variety, coupled with a dearth of diversity in production. Dietary diversity encompasses the adoption of a nourishing, well-rounded, and heterogeneous dietary pattern, thereby guaranteeing the sufficiency of essential nutrients. The principle of dietary diversity is unequivocally endorsed in all national food-based dietary guidelines. Strategies centred on food that aim to combat malnutrition, particularly deficiencies in essential micronutrients, are intricately intertwined with scientifically substantiated dietary patterns. However, these approaches remain disjointed from the existing agricultural production system. The incorporation of promising, yet underutilized, species characterized by their high nutrient density, climate resilience, profitability, and local availability and adaptability plays a pivotal role in enhancing both dietary and production diversity (Mayes *et al.,* 2012).

By delineating the boundaries of suitable areas, scholar inquiry can significantly strengthen the justification for integrating these crops into a holistic approach to climate adaptation. Furthermore, agronomists have the ability to utilize these maps in order to augment their understanding of the existing and future limitations on resources in each specific region and crop. Upon undergoing scrutiny by an agronomist, it becomes evident that maps possess the inherent capacity to expedite the discernment of the most appropriate agronomic methodology that harmonizes with the particular circumstances of the agriculturalist (Mugiyo *et al*., 2022; Mathur and Mathur, 2024).

This study used four Representative

Table 4. Values of niche centroid of three most influential bio-climatic variables pertains to various time-frames and RCPs.

		2050 RCPs				2070 RCPS			
Bio variables	Current	2.6	4.5	6.0	8.5	2.6	4.5	6.0	8.5
Bio-3	-	48.52	49.51	48.34	48.9	50.33	49.27	50	49.78
Bio-4	358.72	-	-	-	-	-	-	-	-
Bio-5	-	386.45	-	-	-	384.27	393.86	499.02	402.63
Bio-6	13.69	154.44	164.78	158.81	166.26	163.17	164.4	-	183.03
Bio-8	-	-	279.84	-	-	-	-	-	-
Bio-13	363.06	-	-	465.02	442.04	-	-	391.42	-

Concentration Pathways (RCPs) to assess crop viability at various concentrations. The RCPs included a large trajectory (RCP8.5), a moderate trajectory (RCP4.5 and RCP6.0), and a small trajectory (RCP2.6). We wanted to determine crop sustainability potential across these trajectories. The environmental adaptation and eco-geographic distribution of underutilized species have been widely recognized in scholarly literature (Williams and Haq, 2002; Mugiyo *et al.,* 2022). Many underutilized species have adapted to inhospitable environments, preserving biodiversity and protecting against risks in an ever-changing ecosystem. Thus, understanding their ecological adaptation and ecogeographic dispersion is crucial to selecting crops for future use (Bow and Haq, 2010).

C. carandas is discussed as a climate-resilient, underutilized crop to examine the factors affecting its domesticated areas, the fundamental niche, and its new viable areas, the realized niche, for its introduction. Koch *et al.* (2022) empirically supported our methods. Their research involves developing an ensemble model to characterize the distribution patterns of *Ensete ventricosum*, a perennial banana species grown only in southwestern Ethiopia. Ratnayake *et al.* (2020) advocated for predictive modelling in the management of Neglected and Underutilized Fruit Species (NUFS) in the light of climate change, supporting our methods. The researchers examined *Aegle marmelos, Annona muricata, Limonia acidissima*, and *Tamarindus indica* species in both present and projected future climates (RCP 4.5 and RCP 8.5) for 2050 and 2070. They used the widely-recognized Maximum entropy (Maxent) Species Distribution Modelling (SDM) approach to predict species distributions. These methods have highlighted the need for climate change adaptation strategies and research to strengthen underutilized fruit crops against climate change.

The current study has furnished a comprehensive nationwide database concerning the geo-tagged spatial distribution of *C. carandas*. This dataset comprises 218 strategically thinned points, and its implications extend to practical assessments of favourable regions for crop cultivation, accurate productivity forecasting, and facilitation of appropriate markets for these under-utilized crops. Moreover, it represents a crucial step towards the development of a user-friendly mobile application, such as "Kirshi-Kisan" (https://play.google.com/store/apps/details?id=com.cropdemonstrate&hl=en&gl=US) by government of India.

The results of our habitat suitability analysis have revealed that the distribution dynamics of this particular species are primarily influenced by temperature-related variables rather than water-related variables such as precipitation. Among temperature variables, isothermality and the minimum temperature during the coldest months have the greatest impact on species distribution. Temperature annual range and the wettest quarter mean temperature affect species distribution less. Moreover, by employing threshold values of the effective temperature variables, such as a minimum temperature of 15°C for the coldest month and an isothermality peak of 50, we can deduce the distribution pattern of this particular species. It becomes apparent that the species is predominantly found in the southern and western regions of the countries, while its presence is notably absent in the northern and eastern regions: In the regions of Gujarat, Karnataka, Tamil Nādu, Andhra Pradesh, and certain areas of Rajasthan. These locations exhibit isothermality, where the diurnal temperature range is half of the annual temperature range. In essence, a numerical value of 100 represents a location where daily temperature fluctuations equal annual temperature variation. However, a numerical value of 50 indicates a location where the 24-hour temperature difference is half of the annual temperature range. According to Kogo *et al.* (2019), environmental factors tend to affect the appropriateness of different regions. Any deviation from these parameters affects crop suitability, whether positively or negatively. In India, *C. carandas* thrives in hot, humid climates. The main factors limiting *C. carandas* growth and development are temperature and seasonal fluctuations (Meena *et al*., 2022).

The variables of urbanization, cultivated land, and grassland have been identified as influential factors in Land Use and Land Cover (LULC). Our analysis has shown that as urbanization increases by 10-20% and grassland expands by 5-10%, the likelihood of suitability for this particular species experiences a gradual but limited decrease. Nevertheless, this particular species demonstrates a remarkable adaptability to thrive within cultivated regions, owing to its significantly higher tolerance for land use and land cover changes. As mentioned, these areas are mostly in Karnataka, Tamil Nadu, and the Western Ghats of Maharashtra and Goa. There are also occasional suitable habitats for this species in Gujarat. We included all the relevant bio-climatic temporal variations and RCPs in our analysis. RCPs were used to identify several Rajasthan locations. However, using LULC predictors, we found widely dispersed optimal habitats for this species in Odisha, Jharkhand, West Bengal, Uttar Pradesh, New Delhi, Uttarakhand, and Jharkhand.

By utilizing the LULC variable, we have successfully documented the highest level of fragmentation within the optimal suitability category, resulting in a notable reduction of up to -38.95% compared to its existing climatic extent. The phenomenon of fragmentation has been previously examined and conceptualized by Rathore *et al.* (2022). LULC changes should significantly impact *C. carandas* distribution in the study region. Urban heat islands show that human activity and ecosystem damage can raise local temperatures, so, species composition may differ between urban and rural areas. Urbanization alters soil properties. Heavy metal and organic matter are higher in urban soils (Wang *et al*., 2016). Bhandari *et al*. (2022) and Padder and Mathavan (2022) quantified how land cover changes adversely affected rice and maize productivity. Unfortunately, this association for underutilized crops has not been studied. This study helped us understand the causes and effects of underutilized crop productivity and its factors.

Understanding niche dynamics is crucial to creating effective conservation strategies (Atwater *et al.,* 2018; Liu *et al.,* 2020). During habitat colonization, species change their niche space, which can maintain, expand, or contract. Variations in the realized niche—all the biotic and abiotic conditions a species is observed in nature—and the fundamental niche—the abiotic conditions needed for positive population growth without biotic interactions—influence these changes (Guisan and Thuiller, 2005). Jezkova and Wiens (2016) found that changing realized and fundamental niches are distinct processes that do not overlap. We simulate *C. carandas* climatic and non-climatic fundamental and realized niche using a precise predictor. The ecological niche hypervolume analysis has shown that *C. carandas* 'climatic niche is larger than its non-climatic niche, which is supported by Bilton *et al*. (2016). This study found that temperature-related factors are most important in determining the phenomenon's spatial range. Niche analysis has shown that the amount of precipitation received during the wettest month is the main factor affecting its ecological niche expansion during the current and projected 2050 climatic timeframe. Niche expansion is regulated by the warmest month's upper limit in 2070.

CONCLUSIONS

This study provides a comprehensive assessment of the habitat suitability of *Carissa carandas* in India, incorporating bio-climatic variables, Greenhouse Gas (GHG) scenarios, and Land Use/Land Cover (LULC) predictors. Using the MaxEnt model, we identified key environmental factors influencing the species' distribution, with temperature-related variables, such as the minimum temperature of the coldest month and isothermality, playing a dominant role. Future climate projections for 2050 and 2070 indicate shifts in suitable habitat, with the southern and western regions of India (including Karnataka, Tamil Nadu, Maharashtra, and Gujarat) continuing to be optimal areas, while habitat fragmentation is expected in the northern and western regions due to climate change and land use changes. The findings underscore the importance of integrating *C. carandas* into climate-resilient agricultural and conservation strategies. Given its adaptability and economic potential, promoting its cultivation in suitable regions can enhance biodiversity, support sustainable agriculture, and provide economic benefits to farmers. However, policy interventions are needed to mitigate the effects of urbanization and land-use changes on its habitat. Future research should focus on refining habitat predictions using additional environmental factors and assessing the socio-economic impact of cultivating this underutilized species.

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ارزیابی مناسب بودن زیستگاه گونه *Carissa carandas* L. در هند با استفاده از متغیرهای زیست اقلیمی، سناریوهای گازهای گلخانه‌ای،و پیش‌بینی‌کننده‌های کاربری زمین و پوشش زمین

مانیش ماتور، و پریت ماتور

چکیده

این پژوهش به منظور ارزیابی مناسب بودن زیستگاه کاریسا کاراندا*carandas* (*Carissa*) ، گیاهی که برای ادغام پایدار آن در کشاورزی تحت شرایط آب و هوایی متغیر بسیار مهم است، در هند انجام شد. ما از مدل‌سازی حداکثر آنتروپی (MaxEnt) برای ارزیابی توزیع گونه‌ها در سناریوهای فعلی و آینده (۲۰۵۰ و ۲۰۷۰) در چهار مسیر غلظت نماینده (Representative Concentration Pathways) شامل (RCPs: ۲.٦، ٤.٥، 6.0 و 8.5) استفاده کردیم. نتایج نشان داد که متغیرهای مرتبط با دما، به ویژه حداقل دمای سردترین ماه (MiTCM، با سهم 48.8% در RCP 2.6 سال 2070) و ایزوترمالیتی (با سهم تا 35/2% در RCP 8.5 سال 2070)، محرک‌های اقلیمی غالب هستند. عوامل کاربری و پوشش زمین (LULC) مانند شهرنشینی (49.8)، کل زمین‌های کشت‌شده (28/1%) و علفزارها (9%) به طور قابل توجهی بر تناسب زیستگاه تأثیر می‌گذارند. در شرایط فعلی، زیستگاه بهینه 4588 کیلومتر مربع را در بر می‌گیرد که تحت سناریوهای LULC %38.95 کاهش می‌یابد. تغییرات پیش‌بینی‌شده زیستگاه نشان‌دهنده افزایش 2.40% تا سال 2070 است، اما کاهش. 11.06درصدی تا سال 2050 با RCP 2.6 را نشان می‌دهد. مناطق جنوبی و غربی، از جمله کارناتاکا، تامیل نادو، ماهاراشترا و گجرات، از تناسب بالایی برخوردارند. تکه‌تکه شدن زیستگاه در شمال و غرب هند به دلیل تغییرات اقلیمی و تغییرات کاربری زمین پیش‌بینی می‌شود. تأکید این یافته‌ها بر نیاز به برنامه‌ریزی حفاظتی پیشگیرانه و استراتژی‌های کشاورزی سازگار با آب و هوا برای بهینه‌سازی کشت *C. carandas* میباشد. سیاست‌گذاران و ذینفعان باید بر حفظ مناطق مناسب تمرکز کنند و درعین حال از بین رفتن زیستگاه ناشی از شهرنشینی را کاهش دهند.