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Predicting habitat suitability of *Illicium griffithii* under climate change scenarios using an ensemble modeling approach

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Climate change is the most significant threat to global biodiversity, risking extinction for many species due to their limited adaptability to rapidly changing environmental conditions, such as temperature, precipitation, and other climate variables. *Illicium griffithii*, an endangered tree with ecological and medicinal value, remains understudied, particularly in Arunachal Pradesh. The aim of the study is to identify key environmental variables influencing the current distribution of *I. griffithii* and to predict the potential distribution under current and future climatic scenarios (SSP245 and SSP585). We used an ensemble modeling approach that integrates five species distribution models (SDMs). After multicollinearity test, we utilized fifteen environmental variables including bioclimatic variables, soil properties, topographical variables, and evapotranspiration to predict the potential distribution of *I. griffithii*. The study revealed that the current distribution is predominantly influenced by isothermality, nitrogen content at 0–5 cm depth, clay content at 0–5 cm depth, and seasonality of precipitation, with a total contribution rate of 42.6%. The ensemble model performed robustly and found to be excellent performance based on AUC of 0.94 and TSS of 0.83. The total highly suitable area for *I. griffithii* spans 722.72 km^2 in the current scenario, primarily located in West Kameng, Tawang, and East Kameng districts. West Kameng stands out as the largest high-suitability area, which covers 592.83 km^2 and contributing a substantial 82.03% of the total suitable area. However, under the SSP585 future climate scenario (2041–2060), projections reveal a concerning decline in highly suitable areas. The area is expected to shrink by over 5.05%, decreasing from 722.72 to 686.25 km^2. The results have highlighted the vulnerability of *I. griffithii* under future climatic scenario. Hence, forest managers should prioritize conserving suitable habitats in West Kameng, Tawang, and East Kameng districts of Arunachal Pradesh by implementing habitat restoration, assisted migration and ex situ conservation strategies that can mitigate climate change impacts.

Keywords *Illicium griffithii*, Species distribution model, Ensemble model, HadGEM3-GC31-LL, Climate change and topographic variables

Illicium griffithii Hook. f. & Thoms. belongs to the family Schisandraceae, known as Himalayan star anise is a threatened aromatic and medicinal plant. The species is distributed across temperate and subtropical forests of Himalayan region, at elevations between 1700 and 3000 m[1]. The species is listed as an endangered species by the IUCN. While, in Arunachal Himalaya the species has been reported as near threatened whereas in Meghalaya it has categorized as critically endangered[2]. This is a large shrub or tree species attaining a height of 3–4.5 m[3]. This species is valued for its phytochemical and medicinal properties. Studies revealed that *I. griffithii* also helps in cancer treatment[4]. In Arunachal Pradesh this species is found in wild habitats of Lower Dibang Valley, Lower Subansiri, Tawang, West Kameng and West Siyang district where the distinctive geography and microclimate

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create an ideal condition for its growth[5]. The properties and distribution of *I. griffithii* are influenced by a range of environmental factors, including geographic location, climate, and soil conditions[6,7]. Climate change, along with habitat modification and degradation, significantly contributes to the rarity of specific species and the decline of biodiversity. Recent studies have extensively studied the impact of climate on distribution of plant species. Climate change can alter the species distribution which results in range shifts, habitat fragmentation and extinction of species. The studies carried out in species like *Magnolia wufengensis*[8], *Polygonum capitatum*[9], and *Tecomella undulata*[10] indicate a drastic fluctuation in their suitable habitats due to temperature and precipitation changes. In this regard, different modeling approaches are beneficial for simulating a range of potential outcomes for target species, supporting decision-makers in minimizing biological consequences and preparing for possible changes.

Species distribution models (SDMs) are most widely used to identify the environmental predictors that determine habitats suitability and to predict the impacts of climate change on various biota[8]. SDMs have a broad range of applications, addressing fields of ecology, geographical ecology, epidemiology, wildlife management, evolution and conservation studies[11,12]. Kaky and Gilbert (2016)[13] reported use of SDM with the MaxEnt algorithm to study the potential of Egypt's protected areas in conserving endemic medicinal plants. They developed individual SDMs for each species and combined them into a single "species richness" layer, which was then compared to the existing protected areas. Temperature emerged as the most influential predictor variable, significantly affecting species distribution[13]. Researchers have employed various SDMs to predict habitat suitability, invasive potential, and environmental drivers of species distributions, as well as medicinal compound accumulation under climate change[14–17]. In recent years, SDM models have been adapted into joint, stacked and ensemble frameworks to address varied research objectives. Common SDM algorithms used include Generalized Linear Models (GLM), Maximum Entropy (MaxEnt), Random Forests (RF), Generalized Additive Models (GAM), and Multivariate Adaptive Regression Splines (MARS)[18,19]. Studies revealed that depending on only one SDM to assess the habitat suitability of a species can lead to substantial deviations in the results by introducing biases and limiting the accuracy of predictions[20]. Wenger et al. (2013)[21] described model uncertainty for ecosystem disturbing alien plant species using same environmental variables and species occurrence data. Adding parameters like vegetation type, edaphic factors, topography, species interactions and the geomorphology are strong predictors that can enhance accuracy for species distribution model[22]. From these drawbacks it is required for enhanced modeling techniques to understand the effects of climatic variables on distributions of species. Also, it is important to understand that while using single SDMs it is important to carefully select the model parameters and heed to other precautions to have a good prediction. As it will not lead to inaccurate results. Using ensemble modeling approach addresses the uncertainty with consensus projection. In ensemble modeling, each model carries both true signal and noise. The true signals capture the relationship between the predictor and response variables, while the noise is introduced by errors and uncertainties in the data and the framework of the model[23]. Ensemble models combined several SDMs to enhance prediction accuracy and reduces biases compared to individual models. Different studies have shown that ensemble models efficiently display habitat suitability and shifts under different climate change scenarios. A study on comparison between ensemble and MaxEnt species distribution modeling it was revealed that MaxEnt, are capable of producing distribution maps of comparable accuracy to ensemble methods[24]. Likewise, another study on ensemble modeling provides consistently high accuracy regardless of background point sampling approach[25]. The application of ensemble models has also been carried out in species like *Castanea dentata*[11]; *Vatica lanceaefolia*[26] and *Taxus wallichiana*[27] that has highlighted their robustness in providing reliable predictions under different climate scenarios. From these findings it can be confirmed that ensemble approaches aid in minimizing biases and maximizing the reliability of predictions. Additionally, climate models combined with SDMs help in obtaining insights into the habitat shifts of species and potential distribution in future under various climate change scenarios[27]. Research indicates that among the various Global Circulation Models (GCMs) within the sixth Coupled Model Intercomparison Project (CMIP6), the Hadley Centre Global Environment Model in its Global Coupled Configuration 3.1 (HadGEM3-GC31-LL) demonstrates the strongest performance for species distribution studies across South and Southeast Asia[28].

Integrating GCM outputs with SDMs supports the exploration of potential species distributions in ecological studies under the impacts of climate change. This approach is particularly valuable for informing adaptive management strategies for endangered species such as *Illicium griffithii*. The objective of the present study was to identify potential distribution for *I. griffithii* in Arunachal Pradesh under different climate scenarios and to determine key environmental factors that affect these distributions. The study hypothesizes that there will be no significant effect of climate change on species distribution of *I. griffithii*. To figure out the habitat suitability and potential distribution of *I. griffithii* we utilized an ensemble model incorporating GLM, MARS, MaxEnt, RF, and SVM. Bioclimatic variables from the HadGEM3-GC31-LL and soil parameters were used as environmental predictors. And we specifically studied climate change scenarios under SSP245 and SSP585 for the periods 2041–2060 and 2061–2080.

Materials and methods

Study area

Arunachal Pradesh, recognized globally as a biodiversity hotspot[29], is located in northeastern India. The state lies between latitudes 26°30' N to 29°30' N and longitudes 91°30' E to 97°30' E, covering an area of 83,743 km² (Fig. 1). Arunachal Pradesh shares borders with Bhutan to the west, China to the north and northeast, Myanmar to the east, and Assam to the south. This unique location makes it a cultural and geographical treasure, rich in natural beauty and heritage. Global recognition acknowledges the state's rich biodiversity and complex ecological zones shaped by its unique geographic and topographic landscape[30]. The region harbours different types of forest, including tropical rainforests, subtropical pine forests, and temperate and alpine vegetation[31].

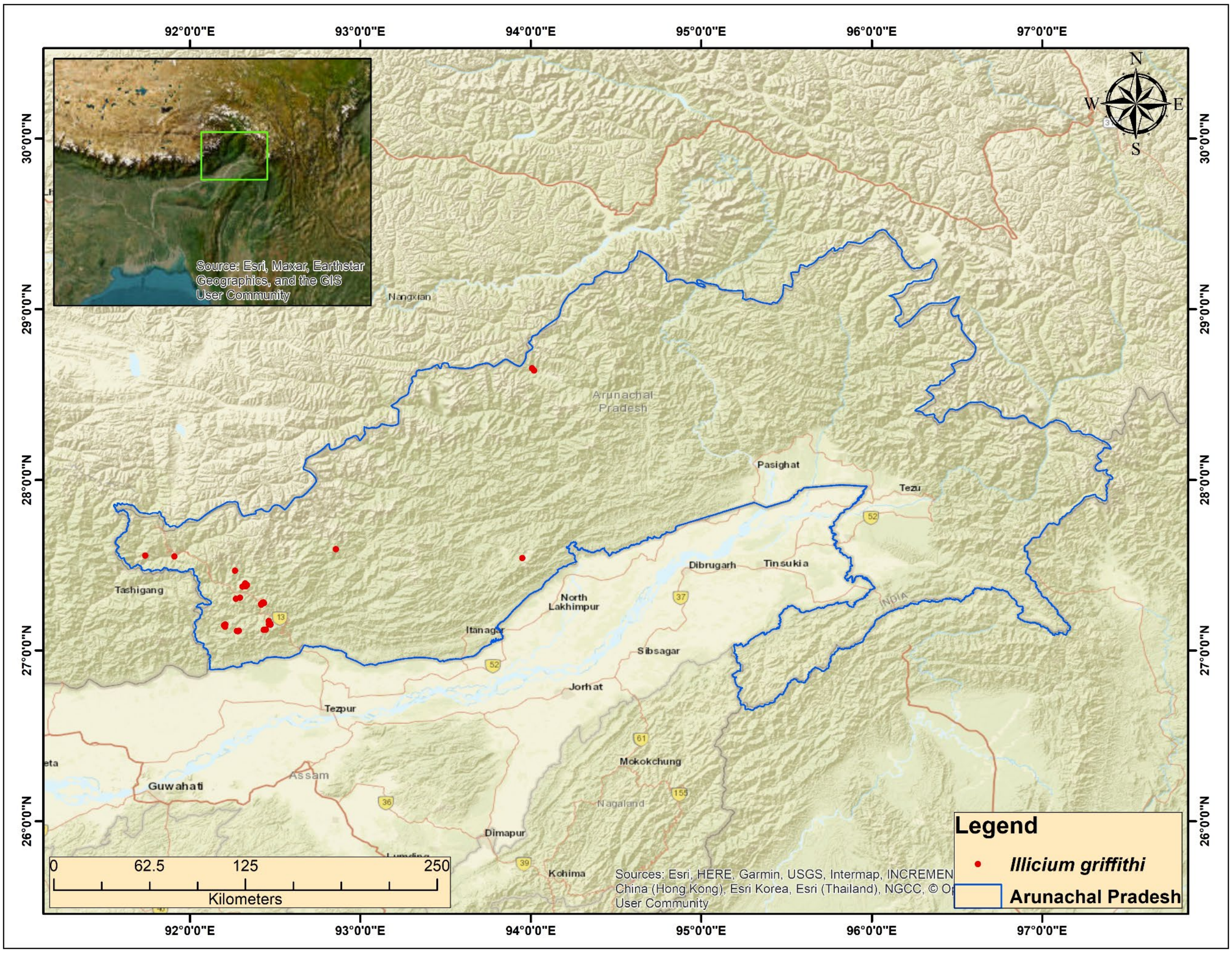

Fig. 1. Map showing the study locations of *Illicium griffithii* in Arunachal Pradesh, India. The Map was generated using ArcGIS 10.6 software (URL: https://www.arcgis.com/index.html, Source: Esri, HERE, Gramin, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri, China (Hong Kong), Esri Korea, Esri (Thailand), NGCC, © OpenStreetMap contributors and the GIS User Community.

These forests are home to an abundance of flora and fauna, with over 500 species of orchids, 650 bird species and numerous endemic plant and animal species[32]. The climate in Arunachal Pradesh changes significantly across the state due to altitude and monsoon patterns. The lowlands have a subtropical climate, while higher areas experience temperate and alpine climates with rainfall reaching up to 3000–5000 mm in some places. The soils of Arunachal Pradesh typically exhibit an acidic nature, accompanied by elevated organic matter levels, constrained nutrient availability, and limited cation exchange capacity[33]. This wide climatic variation creates diverse habitats making it an ideal area for ecological and environmental studies[34]. Previous study has indicated that the altitudinal gradient of hilly regions is characterized by climate variability, which impacts the edaphic properties[35]. Furthermore, fluctuations in altitude influence the soil's organic matter content, thereby regulating factors such as soil moisture, soil erosion, vegetation, and biomass production within the area[36].

Occurrence data

The occurrence points of *I. griffithii* in Arunachal Pradesh were collected from several sources: iNaturalist (https://www.inaturalist.org), India Biodiversity Portal (IBP, https://indiabiodiversity.org), field surveys, and published literature. We initially recorded 42 location points. But, to reduce model overfitting, we utilized the "spThin" package[37] in R 4.3.1[38] to remove the duplicate data within 1×1 km^2 grid. Finally, a total of 31 verified location points of *I. griffithii* were kept for final analysis to generate the potential distribution in the study area using an ensemble algorithm.

Environmental variables

To examine the impacts of climate change on the distribution of *Illicium griffithii*, an ensemble species distribution model was developed using key environmental variables. This analysis incorporated 19 bioclimatic variables sourced from WorldClim (Version 2.0) with a resolution of ~ 1 km^2 (30 arc seconds) (www.worldclim.org)[39]. Additionally, topographic variables, including slope and aspect were derived from a digital elevation model at a resolution of 30 m (https://earthexplorer.usgs.gov/)[40]. Soil variables at 0–5 cm and 5–15 cm depth, such as soil texture (clay, sand, silt), bulk density, cation exchange capacity, soil pH, nitrogen and soil organic carbon were obtained from the International Soil Reference and Information Centre (ISRIC) at a 250 m resolution (https://www.isric.org)[41]. Lastly, evapotranspiration data was downloaded from the MODIS/Terra Net Evapotranspiration database at a resolution of 250 m (www.lpdaac.usgs.gov). This multi-faceted approach allowed for a robust assessment of habitat suitability.

To project future climate change scenarios, we utilized two distinct Shared Socio-economic Pathways (SSPs)-namely SSP245 and SSP585-for the periods 2041–2060 and 2061–2080. SSP245 represents a moderate emissions scenario, while SSP585 reflects a high-emission scenario, assuming minimal mitigation efforts. These updated scenarios, refined from the earlier RCP pathways[42], capture a range of possible futures influenced by varying levels of climate action and societal development.

More specifically, the Hadley Centre Global Environment Model version 3 in its Global Coupled Configuration 3.1 (HadGEM3-GC31-LL) was used. This model represents the UK's contribution to the sixth Coupled Model Intercomparison Project (CMIP6), providing robust simulations to assess potential climate impacts. The multicollinearity among the independent variables was evaluated by computing the variance inflation factor. The final set of predictors was selected based on a variance inflation factor threshold that did not surpass 10[43]. Variable selection was conducted using 'usdm' package in R version 4.3.1[38]. Finally, fifteen variables were selected based on their correlation to mitigate collinearity (Table 1). This step was essential to mitigate the effects of multicollinearity, as highly correlated variables can introduce bias in model predictions[44], thereby reducing the efficiency and increasing the uncertainty of species distribution models[45,46].

Model development and assessment

The predicted distribution of *I. griffithii* was modeled using ensemble algorithms through the "SSDM" package[47] in R version 4.3.1. This approach incorporated five robust algorithms for large-scale distribution modeling, as recommended by Meller et al. (2014)[48]: The five robust algorithms are GLM[49], MARS[50], MaxEnt[51], RF[52], and SVM[53]. Model validation was conducted using tenfold cross-validation, with performance assessed through the Area Under the Curve (AUC) and the True Skill Statistic (TSS). For model construction, 75% of the species presence data was utilized as the training dataset for model building, while the remaining 25% was used as the test dataset to validate the model (Fig. 2). To determine the best-fitting model and generate the ensemble probability surface, an AUC threshold of < 0.75 was set. Validation of the final ensemble model relied on AUC values derived from the Receiver Operating Characteristic (ROC) curve, with model performance categorized into four tiers: poor (0.0-0.7), average (0.7–0.8), good (0.8–0.9), and excellent (0.9-1.0)[54–56]. The TSS scores ranged from − 1 to 1, with values above 0.75 indicating excellent model performance[57]. Furthermore, the TSS score was used to validate the model's accuracy. The final ensemble model was rigorously assessed using the SDMs tool, which provided robust model diagnostics, while the importance of each variable was quantified by its percentage contribution to the overall model performance. These insights helped refine predictions and highlight key environmental factors driving the species distribution. Binary habitat suitability maps were created using the equal test sensitivity (SES) and specificity (SPC) threshold to predict optimal habitats for the target species. Additionally, the variable contributions were evaluated for each model's projection for *I. griffithii* under current potential distribution. Finally, the variable contributions graph was determined by the percent contribution of each variable of the ensemble model[26]. Finally, Zonal statistics were computed using the Raster

Variables	Description	Current	SSP245 (2041–2060)	SSP245 (2061–2080)	SSP585 (2041–2060)	SSP585 (2061–2080)
BIO2	Mean diurnal range (mean of monthly (max temp − min temp))	3.10	2.81	2.79	2.61	2.50
BIO3	Isothermality (BIO2/BIO7) (×100)	2.68	2.46	2.73	2.44	2.55
BIO5	Max temperature of warmest month	7.23	7.05	7.88	6.07	6.33
BIO14	Precipitation of driest month	3.45	2.94	3.32	2.89	3.10
BIO15	Precipitation seasonality (coefficient of variation)	1.83	1.70	1.71	1.75	1.69
Asp	Aspect	1.02	1.02	1.03	1.01	1.02
Slo	Slope	1.39	1.38	1.37	1.44	1.42
ET	Annual evapotranspiration	1.20	1.26	1.22	1.20	1.25
BD_(0–5)	Bulk density (0–5)cm	5.08	7.46	7.94	4.53	5.09
CEC_(5–15)	Cation exchange capacity (5–15)cm	3.92	3.95	4.24	3.81	4.30
Cla_(0–5)	Clay_mean_(0–5)cm	4.84	4.53	4.85	4.37	4.78
Ni_(0–5)	Nitrogen_mean_(0–5)cm	1.52	1.54	1.59	1.57	1.58
San_(0–5)	Sand_mean_(0–5)cm	5.26	5.17	5.30	4.80	4.93
SOC_(0–5)	Soil organic carbon_mean_(0–5)cm	8.38	7.81	8.14	8.10	8.24
SOC_(5–15)	Soil organic carbon_mean(5–15)cm	7.08	6.83	7.00	7.15	7.23

Table 1. Ecological predictor variables selected for modeling the potential habitat of *Illicium griffithii* using VIF.

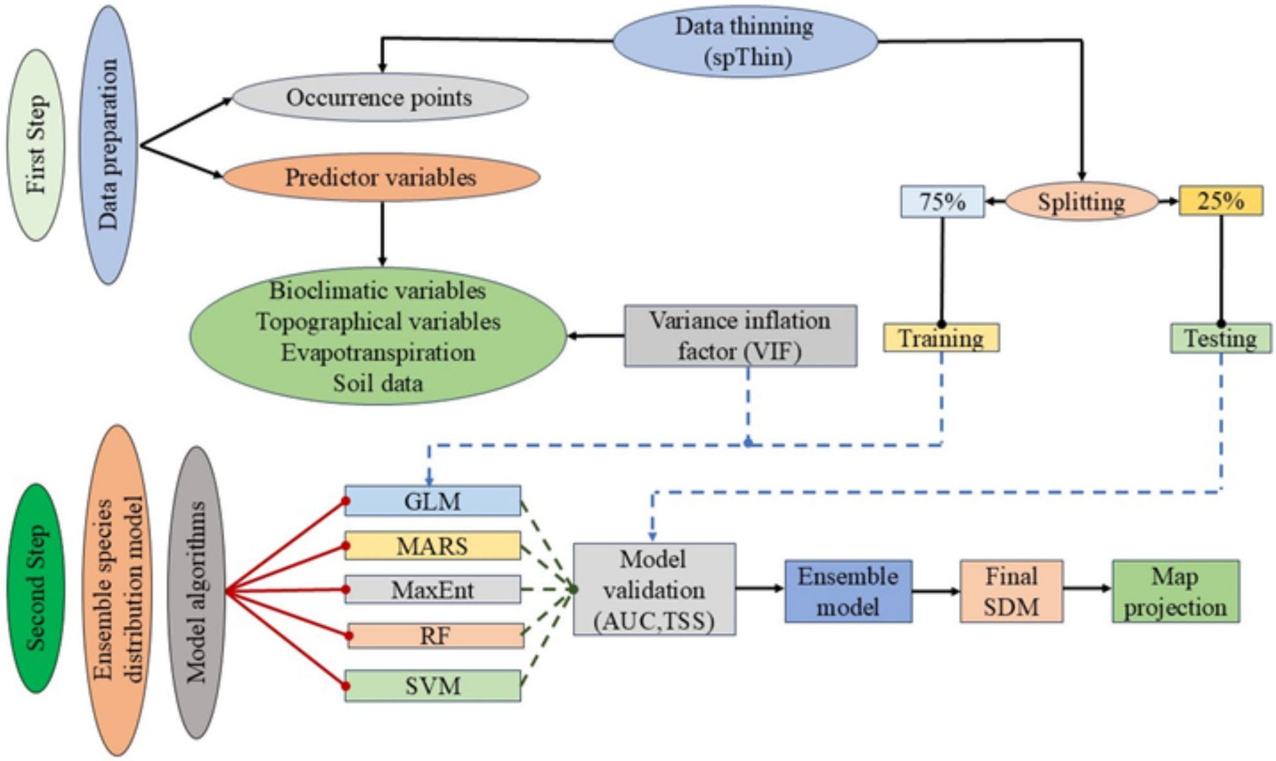

Fig. 2. Methodological flowchart of ensemble species distribution modeling with different SDMs algorithms. The flowchart was created using Microsoft PowerPoint (Microsoft Office Home and Student 2021).

Models	GLM	MARS	MaxEnt	RF	SVM	Ensemble
AUC	0.94	0.87	0.97	0.97	0.96	0.94
Sensitivity	0.90	0.79	0.97	0.93	0.90	0.90
Specificity	0.95	0.92	0.87	0.98	0.93	0.93
TSS	0.85	0.71	0.84	0.91	0.83	0.83

Table 2. Performance evaluation of SDMs using different statistical parameters for the current distribution of *Illicium griffithii* in Arunachal Pradesh, India.

Calculator alongside the Zonal Statistics Tool in ArcGIS 10.6 to enhance the analysis, yielding greater insights into spatial patterns and habitat appropriateness.

Results

Model performance and importance of environmental factors

The results of the final ensemble model, based on the average of 10 replicates, showed excellent performance, with an AUC of 0.94, sensitivity of 0.90, specificity of 0.93, and a TSS of 0.83 (Table 2). MaxEnt and RF achieved the highest AUC score of 0.97, while MARS recorded the lowest at 0.87. The MaxEnt model has a higher sensitivity of 0.97 compared to the RF of 0.93, while MARS exhibits the lowest sensitivity at 0.79. Conversely, RF has a better specificity of 0.98 than GLM of 0.95. Models with TSS values ≥ 0.75 are recognized for their high predictive ability and are considered useful and reliable for niche modeling analysis. The TSS values ranged from 0.91 in RF to 0.71 in MARS. Therefore, in the following analysis we established "SSDM" as the optimum model for *I. griffithii*, as it precisely predicted nearly 90% of the area.

The predictions from the ensemble model explained that the potential distribution of *I. griffithii* is primarily influenced mainly by four key environmental variables as follows: Isothermality (BIO3), Nitrogen (0–5) cm {Ni_(0–15)}, Clay_mean_(0–5)cm {(Cla_(0–5)}, and Precipitation Seasonality (Coefficient of Variation) (BIO15). Among these, Isothermality (BIO3) emerged as the most influential factor, contributing 11.33% to the model's predictions and underscoring its crucial role in defining climatic suitability for this species, followed by Nitrogen (0–5)cm {Ni_(0–15)} contributes (10.94%), Clay_mean_(0–5)cm {(Cla_(0–5)} contributes (10.56%), reflecting the essential role of soil fertility and structure in supporting suitable habitats for *I. griffithii*. While Soil Organic Carbon_mean_(0–5)cm {SOC_(0–5)} has the lowest contribution of 3.17. Notably, among topographical factors, Aspect (Asp) contributed the most (4.13%), highlighting its significance in influencing local sunlight exposure

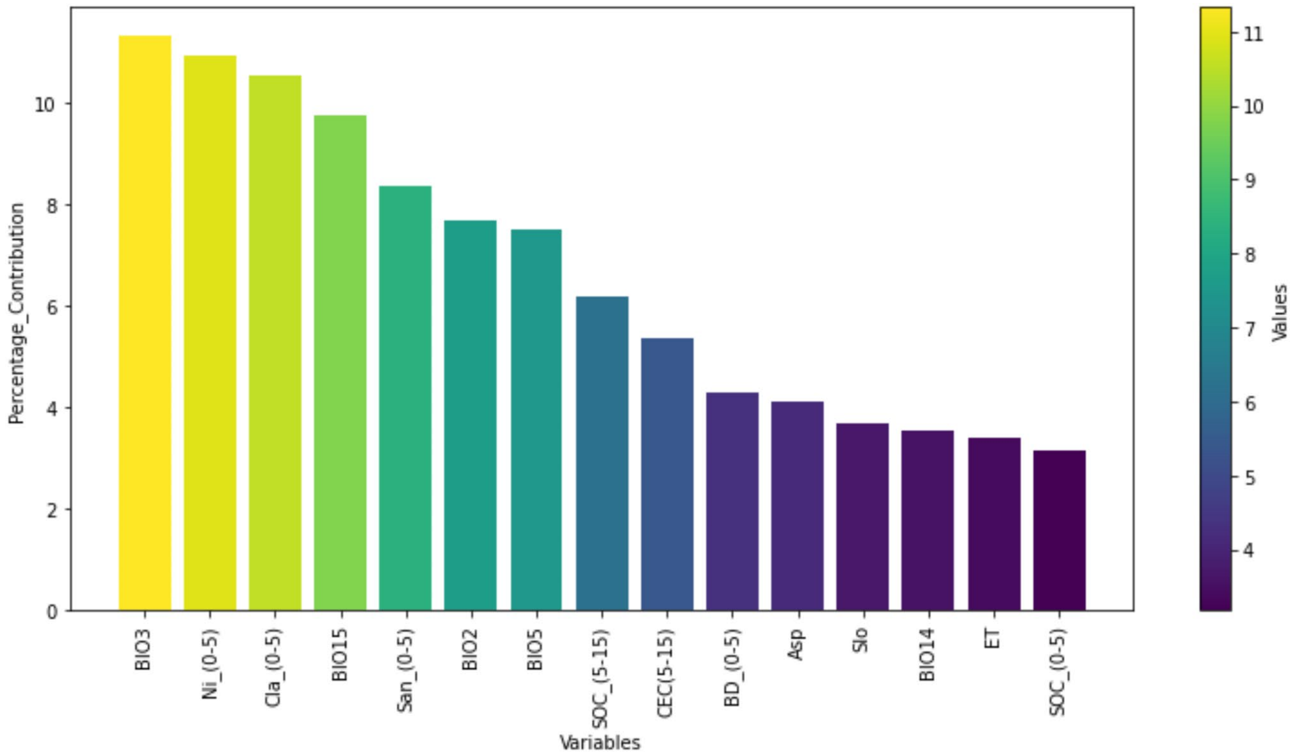

Fig. 3. Variable contributions of different predictor variables for the current distribution of *Illicium griffithii*.

Scenario	High suitability (km^2)	Moderate suitability (km^2)	Low suitability (km^2)	Total suitability (km^2)
Current scenario	722.72	1374.24	7016.36	9113.32
SSP245 (2041–2061)	692.90	1378.05	7309.47	9380.42
SSP245 (2061–2080)	702.89	1302.91	6555.90	8561.70
SSP585 (2041–2061)	686.25	1377.86	6691.10	8755.20
SSP585 (2061–2080)	701.45	1317.34	6054.92	8073.71

Table 3. Areas of projected suitable habitat of *Illicium griffithii* under current and future climatic scenario.

and microclimate. Slope (Slo) also contributed 3.68%, suggesting its role in water runoff and soil stability in the current distribution pattern (Fig. 3).

Modeling habitat suitability of *I. griffithii* under current and future climate scenarios

Future climatic scenarios observed a significant reduction in the highly suitable area for *I. griffithii*. Currently, the highly suitable habitat covers an area of about 722.72 km^2 (0.86% of the total geographical area, i.e., 83,743 km^2). The ensemble model revealed that the potential suitable habitats for *I. griffithii* are approximately 9113.32 km^2, covering 10.88% of the total geographical land of Arunachal Pradesh. The areas of the moderately suitable and the lowly suitable account for 1.64 and 8.38% of the total land area, in the current scenario (Table 3). The highly suitable areas are scattered in the West Kameng, Tawang, East Kameng, Lower Subansiri, Pakke Kessang, and Kamle districts. Meanwhile, moderately suitable areas are more widespread, extending across West Kameng, Tawang, East Kameng, Lower Subansiri, Papum Pare, Pakke Kessang, Kurung Kumey, Kamle, Kra Daadi, Upper Subansiri, Shi Yomi, Siang, Upper Siang, East Siang, Dibang Valley, and Lower Dibang Valley, respectively.

For future potential distribution under the SSP245 and SSP585 scenarios in 2041–2060, the model predicted that there would be 692.90 km^2 (0.83%) of highly suitable area and 686.25 km^2 (0.82%). In 2061–2080, the model projected 702.89 km^2 (0.84%) and 701.45 km^2 (0.84%) of the extremely suitable area under SSP245 and SSP585, respectively. Table 2 shows the change in suitable areas of *I. griffithii* under both scenarios. The model predicts a 4.13% decrease in this area under SSP245 and a 5.05% decrease under SSP585 by 2041–2060. Furthermore, from 2061 to 2080, further reductions are projected, with a 2.74% decrease for SSP245 and a 2.94% decrease for SSP585, compared to current distribution (Fig. 4). West Kameng has the highest suitable area for *I. griffithii* in Arunachal Pradesh, with 592.83 km^2, holding 0.71% as a high suitable area of its total geographical area of 83,743 km^2 in the current scenario. For the period 2041–2060 and 2061–2080 under both the scenarios SSP245 and SSP585 there will be increase in highly suitable area, followed by a decrease for the period of 2041–2060 under SSP585. For the period of 2041–2060 and 2061–2080 there will be a decrease in moderately suitable

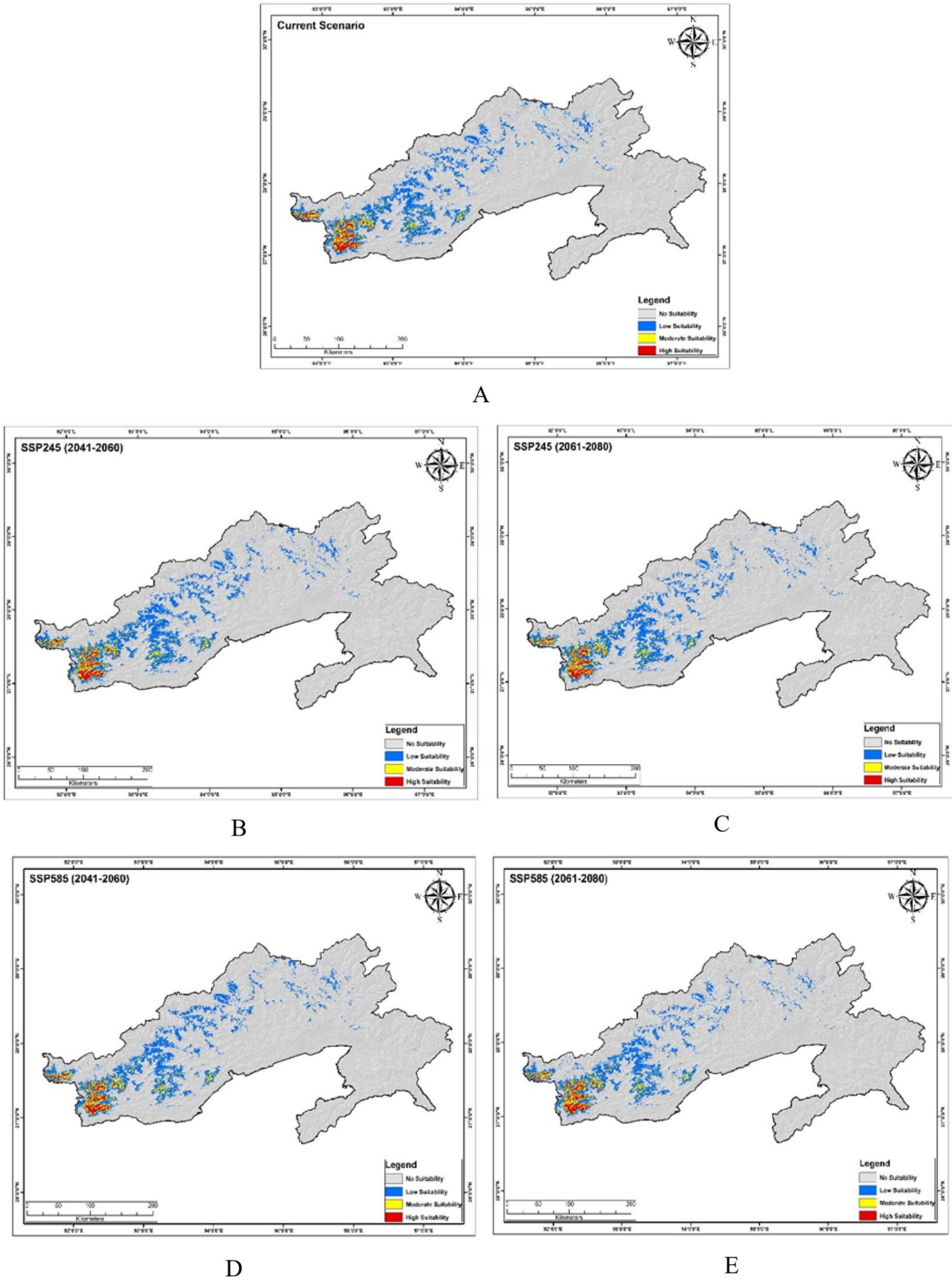

Fig. 4. Potential distribution of *Illicium griffithii* in present and future scenarios (**A**) current scenario, (**B**) SSP245 (2041–2060) scenario, (**C**) SSP245 (2061–2080) scenario, and (**D**) SSP585 (2041–2060) scenario, (**E**) SSP585 (2061–2080) scenario. The map was generated using ArcGIS 10.6 software (URL: https://www.arcgis.com/index.html).

areas under both the scenarios. Whereas, under SSP585 for the period 2041–2060 a maximum decline was documented in low suitable area as compared to the present scenario. Tawang is the second highest district to cover the highly suitable area of *I. griffithii* with an area cover of 115.48 km^2 (0.14%). It was noted that the highly and moderately suitable area of Tawang will decrease during 2041–2060 and 2061–2080, with highest decline logged in highly suitable area with an increase in low suitable areas under both scenarios. In the districts of East Kameng, and Pakke Kessang, there will be an initial increase in suitable areas of *I. griffithii* under SSP245 and SSP585 between the years 2041–2060 and 2061–2080. While in Kamle, a decline in highly suitable areas is projected under SSP245 and SSP585 scenarios during both 2041–2060 and 2061–2080. However, in Lower

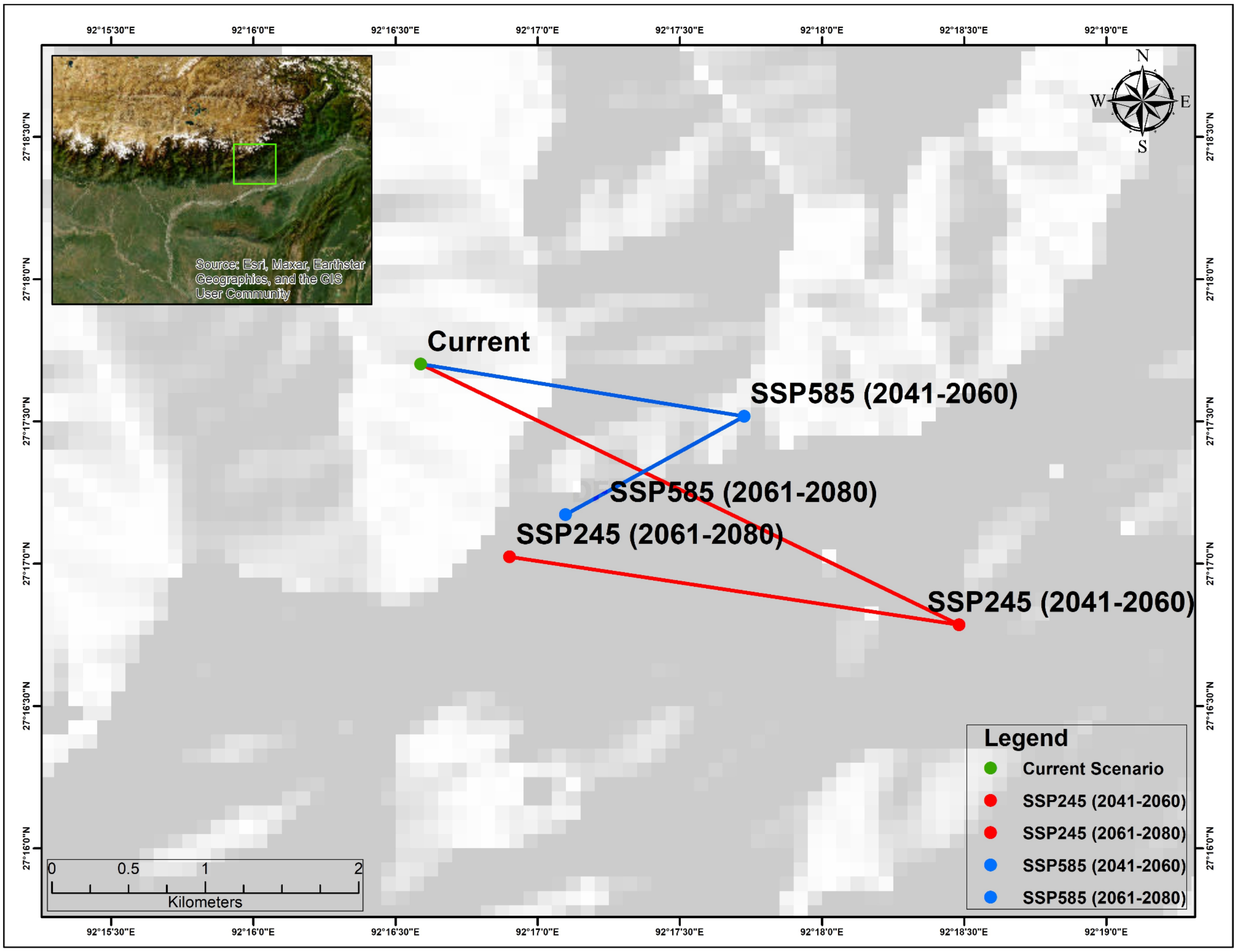

Fig. 5. Central displacement of *Illicium griffithii* under ecological regionalization. The map was generated using ArcGIS 10.6 software (URL: https://www.arcgis.com/index.html).

Subansiri, there will be an initial increase in highly suitable areas followed by a decrease under the same scenarios and time frames. In other districts Lower Siyang, Lepa Rada, Namsai, Tirap, and Longding aren't predicted to exhibit any suitable habitat for the species *I. griffithii*.

Centroid shifts in high suitable areas of *I. griffithii*

The ensemble species distribution analysis for *I. griffithii* reveals that the centroid locations have shifted consistently across all periods in both climate change scenarios (SSP245 and SSP585). During the current period, the centroid of the highly suitable area is situated in the West Kameng district of Arunachal Pradesh (27.29°N, 92.27°E). Under the SSP245 scenario, the core distribution migrates southeast within the West Kameng district, shifting 3.90 km by mid-century (2041–2060) to 27.27°N, 92.30°E. By the late century (2061–2080), the centroid shifts 2.97 km northwest, reaching 27.28°N, 92.28°E. Similarly, under the SSP585 scenario, the centroid moves 2.13 km southeast by mid-century (2041–2060) to 27.29°N, 92.29°E. By the 2070s, it shifts northwest by 1.33 km to 27.28°N, 92.28°E. In both climate scenarios, the trends in centroid displacement were opposite although consistent directional pattern, reflecting notable shifts within the West Kameng district over time (Fig. 5).

Discussion

The ensemble model enables the simultaneous evaluation of multiple species, model types and sampling approaches[58]. In our study, the ensemble model has exhibited the most reliable variables for ecological niche modeling of *I. griffithii*. From the ensemble model performance, AUC showed a maximum score subsequently high sensitivity, specificity and TSS. AUC can differentiate between suitable and unsuitable habitats for the species. On the other hand, sensitivity and specificity can predict the presence or absence of a species[59]. The TSS value of more than 0.75 suggested the high predictive accuracy of the model. Different studies considered AUC and TSS as the most effective methods to measure the predictive performance of the model[60–62]. In species distribution studies, RF and MaxEnt models are considered popular machine learning models[63]. Bedair et al., (2023)[64] reported that MaxEnt's high predictive performance has led to its widespread use and treated as the default method for SDM. However, based on the individual algorithms, MaxEnt and RF were the most reliable models having equal AUC score of 0.97. Sensitivity was maximum in MaxEnt (0.97) and specificity in RF (0.98). MARS exhibited the lowest performance with an AUC of 0.87 and sensitivity of 0.79. GLM, on the other hand, achieved the lowest specificity. Based on the model algorithms in the current scenerio, it can be revealed that the ecological distribution of the species and relative adequacy can be best performed for *I. griffithii*. However, the accuracy of prediction by ecological models may vary using the same algorithm[65]. In our study, SSDM predicted 90% of the study area, proclaiming its ability to minimize biases associated with the modeling techniques that provide high accuracy and reliability of habitat suitability for *I. griffithii*. SSDM is considered to be more reliable and informative for species distribution predictions[66] and it can also predict species assemblage as compared with a point-to-grid map or a MEM[45]. The environmental variables which comprise climate, soil and topography have a significant influence on the distribution of *I. griffithii*. These environmental variables highlight the complex interconnection of environmental factors which plays a crucial role in the conservation of the species. In determining climatic suitability, isothermality (BIO3) accounted for 11.33%, making it the most dominant factor in knowing the distribution of *I. griffithii*. Other studies[67–69] also found that isothermality played a significant role in determining the species distribution pattern. Hence, temperature variation in the study region can significantly impact the species. Other ecological predictor variables, like Nitrogen (0–5 cm) with 10.94% and clay mean (0–5 cm) with 10.6%, are also very important as they provide information on the habitat's soil fertility and texture for *I. griffithii*. Study on *Juniperus phoenicea* reported that clay content are the most important factors limiting the potential distribution of the species[70]. The study revealed that topographical features are less significant as compared to climatic and soil variables. Aspect (4.13%) and slope (3.68%) were important factors in determining the distribution of *I. griffithii* in terms of topographical features. The complex interaction of climate, soil and topography are important parameters that are critical in determining the habitat suitability of *I. griffithii*.

SDM have become one of the important models in relation to studying the shift in species range due to global climate change[71,72]. In order to generate habitat suitability models for endangered species, a sufficient observational data is required[48]. In our study, we have measured the potential distribution in present and future scenarios in the whole state of Arunachal Pradesh. The study revealed that the potentially suitable area of *I. griffithii* is 9,113.32 km² which constitutes 10.88% out of the total area of 83,743 km² in Arunachal Pradesh. However, moderately suitable area and lowly suitable areas constitute 1.64 and 8.38%, respectively. Likewise, the highly suitable habitat accounts for 0.86% in the region. The variation in the suitable area can be related to climate change and anthropogenic activities. Previous studies on the same species reveal that the species has a low population, poor germination and the seeds remain dormant for four to five months due to biotic factors[3]. The regeneration growth of the species is also poor due to unchecked exploitation of the species[73]. *I. griffithii* is regarded as a valuable spice in the region[74], contributing a good source of income[75]. However, anthropogenic disturbances are the major threat to its existing population[76]. These findings line up with our study which show the decrease in species distribution under SSP245 and SSP585. The findings revealed substantial decreased of highly suitable areas of *I. griffithii* in both scenarios, specifically between 2041-2060 and 2061–2080. Compared to the current scenario, the habitat of *I. griffithii* is expected to reduce by 4.13 and 5.05% by 2041–2060. Additionally, projections indicate a decrease by 2.74 and 2.94% in the area during 2061–2080. These projections emphasize the vulnerability of *I. griffithii* under climate change scenarios. As per district-wise analysis, West Kameng holds the largest highly suitable area followed by Tawang, East Kameng, Pakke Kessang, Kamle and lower Subansiri. In West Kameng, under SSP245 and SSP585 scenarios, there is an increase in suitable areas in the early phase, but in the later phase, a decline is projected under SSP585. Future scenarios in Tawang predict a significant decline in suitable areas with an expected increase in low suitable areas. This may result in decline in the availability of species habitat in future scenarios. In East Kameng, Pakke Kessang and Lower Subansiri, the projections of suitable habitats change over time. In both scenarios, they increase in the early period followed by a decline in the later phases. Future climatic scenarios are expected to shift significantly the distribution of species potentially resulting to a high risk of habitat loss. Projections with the optimistic SSP245 scenario for 2041–2060 show a highly suitable areas showing a significant reduction of 0.03%. On the other hand, the severe pessimistic SSP585 scenario predicts an even greater loss with a drop of 0.04% from the total geographical area of 83,743 km^2. In 2061–2080, both SSP245 and SSP585 scenarios project an additional decline of 0.02% compared to the current scenario. These trends highlight the pressing need for proactive and urgent conservation measures to mitigate the impacts of habitat loss under changing climatic conditions. The current suitable area may shrink in the future projected climatic conditions, which means the current habitat may not effectively protect the species in long-term survival. Hence, identifying the important habitats will contribute in conservation planning of the species. It is highly recommended to take adaptive measures to climate change including management of present habitats and ex situ conservation of the species in climate-suitable areas for conservation. The study does not provide information on species interactions which may influence species distributions. However, the study work depicts the first comprehensive assessment of the potential distribution of *I. griffithii* under current and future climate scenarios. This study provides baseline data to the scientific community reflecting the profound impact of climate change on the species' potential distribution under future climatic scenarios.

Conclusion

Under future climate scenarios, the study reveals a significant reduction in the habitat suitability of *I. griffithii*. Projections for the period of 2041–2060 indicate that there would be a decrease in the area of highly suitable habitat. Under the SSP585 scenario, the maximum reduction is expected to be 36.47 km^2, while under SSP245, a reduction of 29.82 km^2 is projected. These findings highlight the negative impacts of climate change on the distribution of species. The ensemble model for the species *I. griffithii* provides key insights for conservation planning, identifying areas that may remain viable under future climate conditions. These results are crucial for formulating strategies to protect *I. griffithii*, particularly in the Himalayas of Arunachal Pradesh, where habitat loss and fragmentation due to anthropogenic activities pose a significant threat to its survival. Given these challenges, SDMs serve as essential tools for predicting potential range shifts and understanding the species' current and future habitat suitability. Through a comparative analysis of the models' outputs, we concluded that Maximum entropy (MaxEnt) and Support vector machines (SVM) emerged as the most effective modeling approaches for predicting the distribution of *I. griffithii*. The study also suggests the need to use multiple models to enhance the precision and consistency of predictions, making it a valuable approach for assessing climate change impacts on species distributions. Our predicted model shows a slight northward shift of highly suitable areas due to climate change. Furthermore, given the likelihood of climate change, it is highly probable that the most suitable areas will undergo significant changes. The predicted minimal rate of change in these factors could make climate change a time-consuming process. Therefore, minor variations in the factors may influence the species range and its ecological interactions significantly and hence its constant monitoring is crucial to ensure its conservation.

Recommendations

A significant decline in suitable habitats of *I. griffithii* has been observed under current and future climatic scenarios due to climate change. For ensuring the conservation of the species forest managers should prioritize the management and habitat restoration of the suitable habitats. Implementing long-term ecological monitoring and ex situ conservation of *I. griffithii* can help in assessing population trends and habitat changes over time. Also, community-based conservation initiatives involving local stakeholders, ecologists and climate researchers can be imperative for conservation strategies. For immediate action, it is necessary to formulate policies integrating climate adaptation measures to mitigate habitat loss and secure the survival of *I. griffithii* in the face of climatic challenges.

Data availability

Data is provided within the manuscript.

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Author contributions
Data collection and analysis for this study were led by AB, AB, BT, and BSD. AB, KS, and SH contribute to the development of machine learning models and interpreting the results. ALD, SB, BPS, VC, AP, and PB focused on writing and revising the manuscript. All authors are equally contributed to the manuscript.

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Declarations

Competing interests
The authors declare no competing interests.

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