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Habitat suitability modelling and range change dynamics of *Bergenia stracheyi* under projected climate change scenarios

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Prioritizing native and endemic species for conservation is fundamental to achieve broader objectives of safeguarding biodiversity, as these species are vulnerable to extinction risks. Forecasting the climatic niche of these species through species distribution models can be crucial for their habitat conservation and sustainable management in future. In this study, an ensemble modelling approach was used to predict the distribution of *Bergenia stracheyi*, a native alpine plant species of Himalayan region. The results revealed that the distribution of *B. stracheyi* is primarily influenced by Annual Mean Temperature (Bio1) and Annual Precipitation (Bio12). Ensemble model predictions revealed that under the current climatic conditions, the suitable habitats for *B. stracheyi* are distributed across higher elevations of Jammu and Kashmir and future ensemble model predictions indicate that, across all future climatic scenarios, the majority of the currently suitable habitats will remain suitable for the species. The model predicts a significant expansion in suitable habitats for *B. stracheyi*, particularly under more severe climate change scenarios (RCP8.5). However, some areas currently identified as suitable, including parts of the Pir Panjal range and Mirpur (Pakistan), are projected to become unsuitable for the species in the future. These shifts in plant distribution may have far-reaching consequences for ecosystem functioning and stability and the services provided to human communities. Additionally, these shifts may lead to mismatches between the plant phenological events and pollinators potentially causing more ecological disruptions. Thus, the predicted range shifts in the distribution of *B. stracheyi* highlight the importance of local conservation measures to mitigate the impacts of climate change.

KEYWORDS

native and endemic, medicinal plants, climate change, ensemble modelling, range change, Himalayan region

1 Introduction

Global biodiversity is declining at an unprecedented rate and with nearly a million plant and animal species at risk of extinction—a threat projected to worsen over the next few decades (Turnhout and Purvis, 2020; Palombo, 2021). This decline in biodiversity results from both anthropogenic and natural causes. Among various drivers, climate change is perceived as one of the most severe threats to biodiversity (Ripple et al., 2017; Arneth et al., 2020; Roman-Palacios and Wiens, 2020; Verrall and Pickering, 2020; Wani et al., 2024a). In the modern anthropocene era, climate shifts pose a serious threat to the overall functioning and stability of ecosystems (Wan et al., 2016) and have long-term effects, leading to ecological niche shifts in various plant species (Lenoir et al., 2020). Changes in regional climate such as alteration in precipitation patterns and humidity, and reduced snow cover significantly affect biodiversity of that region as climate variables primarily govern the geographic range of species distributions (Weiskopf et al., 2020; Pepin et al., 2022; Shakoor et al., 2023; Wang et al., 2024). While several species suffer from climate change, but some are able to adapt to climate change by moving to more favorable locations (Vitasse et al., 2021; Manes et al., 2021a) or by utilizing adaptive genetic systems or phenotypic plasticity to withstand environmental changes (Anderson and Song, 2020; Pazzaglia et al., 2021). The distributional ranges of species are altered due to their cumulative adaptive responses to climate change (Taheri et al., 2021). The steadily rising concentration of greenhouse gases threatens the survival of various plant species, and disrupts the stability and functionality of ecosystems worldwide (Kumar et al., 2024; Chaudhry and Sidhu, 2022; Shrestha et al., 2022; Zandalinas et al., 2022). However, the Himalayan biodiversity hotspot is particularly vulnerable to climate change with three-fold faster warming than the global average (Shrestha et al., 2012). Climate is expected to affect the growth, phenology, and distribution of Himalayan plants, posing significant challenges to their survival in the future (Sarkar et al., 2024; Rana et al., 2024; Mishra et al., 2024). Further, climate change is closely linked to shifts in species distribution (Permesan, 2006; Sekar et al., 2024), thus highlighting the urgent need to understand the dynamics of species distribution and ecological niches (Javeed et al., 2024). Furthermore, under these critical scenarios prioritizing native and endemic species for conservation is essential to achieving broader biodiversity conservation goals, as these species are vulnerable to extinction (Manes et al., 2021b). Thus, forecasting the climatic niche of native and endemic species using species distribution models (SDMs) is crucial for habitat conservation and the sustainable management of species in the future (Profirio et al., 2014).

Species distribution modelling (SDM) is a useful technique for predicting range shifts and identifying habitats suitable for species conservation in response to climate change (Zellmer et al., 2019). SDM has significant potential to support adaptive conservation initiatives and ultimately contribute to biodiversity conservation (Guisan et al., 2013). SDM is an emerging field in ecology for predicting species distributions and has gained increasing importance in the context of growing awareness of environmental change and its ecological consequences (Miller, 2010). It allows for the assessment of a wide range of biodiversity phenomena, including potential geographic distributions, future distributions under climate change scenarios, species invasions, crop damage by pest organisms, biodiversity conservation priorities, and species range shifts (Javeed et al., 2024). Various algorithms are used in SDM typically integrating the species occurrence data and environmental variables to identify suitable habitats (Kaky et al., 2020; Frans et al., 2022). Endemic species have a limited geographic range, making them more vulnerable to extinction due to natural and anthropogenic drivers (Kraus et al., 2023; Wani et al., 2023). Given this susceptibility of endemic plants, information on population status, distribution range and threats has significant conservation implications (Abro et al., 2024). It is therefore imperative to understand the distribution of endemic species and SDMs are increasing recognized as a valuable tool to predict suitable habitats under current and future climatic scenarios (Qazi et al., 2022). In the present study, an ensemble of multiple algorithms was used to predict the distribution of *Bergenia stracheyi*, a native alpine plant species of the Himalayan region. The present study aims to: a) predict the current distribution of *B. stracheyi* using an ensemble modelling approach; b) predict the distribution of *B. stracheyi* under changing climatic scenarios; c) assess the range shifts in the distribution of *B. stracheyi* under anticipated climate change; d) identify the most important bioclimatic variables determining the distribution of *B. stracheyi*.

2 Materials and methods

2.1 Study area

Jammu and Kashmir, formerly a state of India (bifurcated into two Union Territories, Jammu-Kashmir and Ladakh) lies between the coordinates 32°17′ to 37°20′ N and73°25′ to 80°30′ E with an elevation range of 225-8,253 m asl (Figure 1). Climatically, the study area is divided into sub-tropical (Jammu), temperate (Kashmir) and cold desert (Ladakh) in south, middle and the east, respectively. Owing to its varied topography, altitude, and climate, the region supports a rich biodiversity and provides a complex habitat for numerous rare, endemic, and threatened plant species. However, several plant species have faced threats over the years due to habitat loss, fragmentation, deforestation, invasive species introduction, overgrazing, overexploitation, land-use changes, a large influx of tourists, road construction, and political unrest (Pant and Pant, 2011; Tali et al., 2019; Mir et al., 2020; Wani et al., 2022a). A total of 429 species of phanerogams, representing 256 genera in 87 families, have been documented in different threat assessment studies in the State (Hamid et al., 2020). This indicates that a significant portion of state's biodiversity is threatened by the anthropogenic disturbances and climate change (Pant and Pant, 2011; Khuroo et al., 2020).

2.2 Target plant species

Bergenia stracheyi (Hook.f. & Thomson) Engl., a member of the family Saxifragaceae is a herbaceous plant native to the Himalayas,

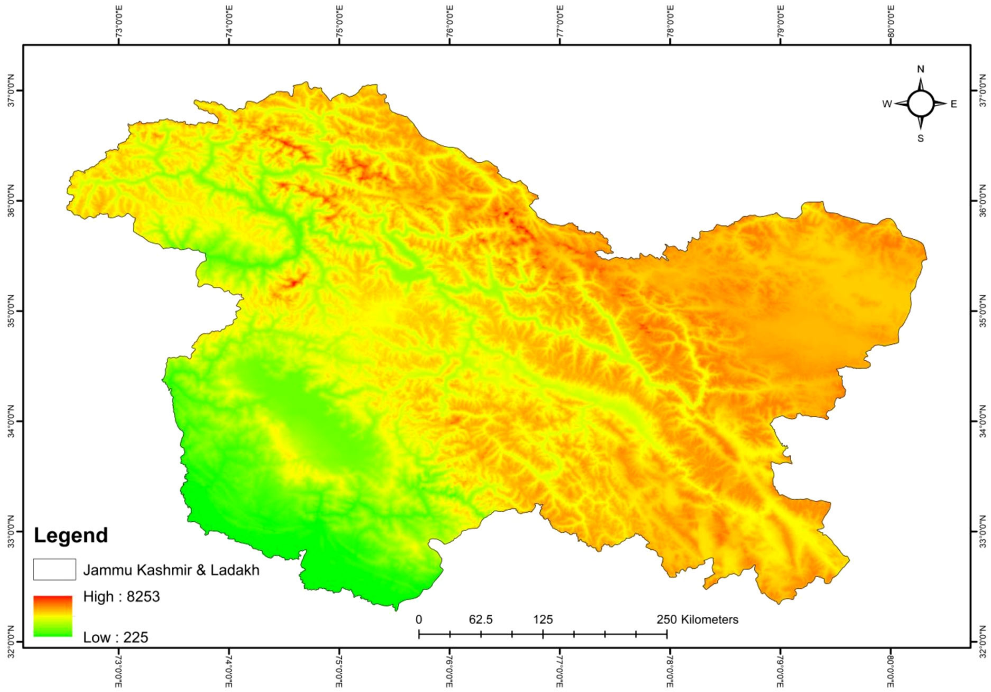

FIGURE 1
Location and elevation map of the study area.

from Afghanistan to Uttarakhand. It is particularly common in the western Himalaya, occurring at elevations between 3300 and 4800 m asl (Tiwari et al., 2017; Flowers of India assessed on 26th November, 2024). *B. stracheyi* thrives in nutrient rich soil, preferring shady habitats, often growing within rocks crevices (Figure 2). Morphologically, it is distinguished by its massive rootstock reserve and broad petiolar sheath (Chauhan et al., 2016). The rhizomes of *B. stracheyi* are solid, dark brown, and longitudinally grooved. These rhizomes are traditionally used to treat ailments such as renal calculi, and burns; while their astringent and laxative properties make them beneficial for digestive disorders (Siddiq et al., 2012; Tiwari et al., 2017; Ali et al., 2014). Owing to the presence of biologically active compounds like bergenin (Siddiq et al., 2012), *B. stracheyi* holds significant medicinal value, particularly in Ayurveda and Unani healthcare systems (Karki et al., 2021). Additionally, plant extracts have been reported to exhibit anti-oxidant and anti-microbial properties (Karki et al., 2021).

FIGURE 2
Field photographs showing the Habitat **(A)** and morphology **(B)** of *Bergenia stracheyi*.

2.3 Species occurrence data

A total of thirty-six occurrence records of *B. stracheyi* were collected through intensive field surveys conducted between 2018 and 2023 and was further supplemented with data from the Global Biodiversity Information Facility (GBIF) (http://www.gbif.org accessed 05 June 2024) using the '*gbif*' function available in '*dismo*' package in R statistical software version 4.0.3. A crucial pre-processing step in species distribution modeling (SDM) is spatial rarefaction, particularly when occurrence points are unevenly distributed or in clustered within the study area. Occurrence records are often collected from easily accessible locations, such as areas near roads, human settlements, or well-studied sites, leading to the spatial bias (Boria et al., 2014; Ahmad et al., 2019). If left unaddressed, spatial bias can lead to over-predictions in certain regions, resulting in flawed model outputs (Boria et al., 2014; Wani et al., 2022b). To mitigate this, occurrence records were spatially rarefied, removing autocorrelated points and reducing multiple occurrences to a single point within 1×1 km grid. After spatial rarefaction, a final geo-referenced dataset with 31 occurrence points was compiled for modelling the distribution of *B. stracheyi*.

2.4 Environmental data

Nineteen bioclimatic variables were obtained from the WorldClim database, ver. 1.4 (http://www.worldclim.org) at a 1 km spatial resolution to model the current distribution of *B. stracheyi* (Table 1). Future climatic data for two representative concentration pathways (RCP 4.5 and RCP 8.5) for the time periods 2050 and 2070 was sourced from the 5th assessment report (AR5) of the Intergovernmental Panel for Climate Change (IPCC). The Hadley Global Environment Model 2-Earth System (HADGEM2-ES) was selected due to its ability to simulate enhanced climate induced ecosystem and hydrological processes (Chakraborty et al., 2016). HADGEM2-ES is widely recognized for its robust simulation capabilities and has been extensively used in climate research to project future climatic conditions under various greenhouse gas emission scenarios. It has been widely applied in predicting species distributions in the Himalayan region (Gajurel et al., 2014; Chakraborty et al., 2016; He et al., 2019; Li et al., 2020; Singh et al., 2022). The data represents simulations for four representative concentration pathways (RCP2.6, RCP4.5, RCP6.0, and RCP8.5), depicting optimistic and pessimistic approaches for the years 2050 and 2070 (Moss et al., 2010). RCP 4.5 assumes that greenhouse gas emissions will be moderate at first then stabilize as a result of substantial mitigation efforts and by the year 2100, radiative forcing is expected to stabilize at about 4.5 W/m². Contradictory, RCP 8.5 assumes a continued high use of fossil fuels and the absence of major efforts to reduce emissions and projects radiative forcing to reach 8.5 W/m² by 2100 (Farooq et al., 2023; Chanzi et al., 2023).

TABLE 1 List of 19 bioclimatic variables used for habitat suitability modelling of selected plant species downloaded from WorldClim database, ver. 1.4 (http://www.worldclim.org).

Variable	Description	Temporal scale
Bio1	Annual Mean Temperature	Annual
Bio2	Mean Diurnal Range	Variation
Bio3	Isothermality	Variation
Bio4	Temperature Seasonality	Variation
Bio5	Maximum Temperature of Warmest Month	Month
Bio6	Minimum Temperature of Coldest Month	Month
Bio7	Temperature Annual Range	Annual
Bio8	Mean Temperature of Wettest Quarter	Quarter
Bio9	Mean Temperature of Driest Quarter	Quarter
Bio10	Mean Temperature of Warmest Quarter	Quarter
Bio11	Mean Temperature of Coldest Quarter	Quarter
Bio12	Annual Precipitation	Annual
Bio13	Precipitation of Wettest Month	Month
Bio14	Precipitation of Driest Month	Month
Bio15	Precipitation Seasonality	Variation
Bio16	Precipitation of Wettest Quarter	Quarter
Bio17	Precipitation of Driest Quarter	Quarter
Bio18	Precipitation of Warmest Quarter	Quarter
Bio19	Precipitation of Coldest Quarter	Quarter

In ecological modeling, multi-collinearity among predictor variables can negatively impact model performance, leading to over-fitting, poor generalization, and unreliable results (Dormann et al., 2013a; Amiri et al., 2022). In particular, highly correlated environmental variables can induce redundancy, making it difficult to isolate the individual effects of each variable on the species distribution. To mitigate the impact of multi-collinearity and enhance the robustness of the model, Pearson correlation analysis was used to assess the degree of autocorrelation between bioclimatic variables. For correlation analysis, values for bioclimatic variables for all occurrence points were extracted by using "extract values to points" in ArcGIS 10.8. The exported data was imported into ORIGIN 10.0 software for correlation analysis. Pairs of variables with a correlation coefficient (r) greater than 0.7 were considered highly correlated. Following Peterson et al. (2011), only one variable from each highly correlated pair was retained for modelling, while the others were excluded. This approach ensured that only the most independent variables contributed to the model, minimizing collinearity and improving accuracy. The same set of least correlated variables was used to predict the current and future distribution of *B. stracheyi*.

2.5 Modelling technique

Current and future distribution modelling and forecasting were performed using the '*biomod2*' package, designed for ensemble species distribution modeling (Thuiller et al., 2009), within R statistical software (v 4.0.3; R Core Team, 2021). It provides a comprehensive framework for modelling species distributions and predicting their potential geographic ranges under current and future environmental conditions. Widely used in ecology and conservation biology, it is valued for its flexibility, ease of use, and ability to integrate multiple modeling algorithms (Zhang et al., 2024). By allows users to combine results from multiple algorithms to create ensemble models, *biomod2* enhances prediction reliability and reduces biases associated with individual models (Gu et al., 2024). In the present study, an ensemble of 10 algorithms viz., Generalized Linear Model (GLM), Generalized Additive Models (GAM), Generalized Boosted Models (GBM), Classification Tree Analysis (CTA), Flexible Discriminant Analysis (FDA), Artificial Neural Networks (ANN), Maximum Entropy (MaxEnt), Multivariate Adaptive Regression Splines (MARS), Random Forest (RF), and Surface Response Envelope (SRE) were used to create species distribution maps.

One thousand pseudo-absences within the study area were generated and to lessen potential sample bias in the generation of pseudo-absences, the procedure was replicated three times following Wu et al. (2024). For model calibration, 80% of the occurrence data was used for training and 20% was used for testing and the process was repeated thrice to reduce uncertainty. Model performance was assessed using cross validation using Area under Curve (AUC), and True Skills Statistics (TSS) as evaluation metrics. The AUC evaluates the performance of a binary classification model by analyzing the Receiver Operating Characteristic (ROC) curve. AUC values range from 0-1, with higher values indicating better model discrimination between presence and absence (Wani et al., 2024b). The TSS assesses the model accuracy by considering both omission and commission errors. Its value ranges from -1 to +1, where higher values indicate better model performance (Freitas et al., 2019). Ensemble model for each climatic scenario and time period combination were constructed using two approaches: committee averaging and weighted mean. The ensemble modelling process incorporated all repetitions and pseudo-absence sets from the algorithm with the highest accuracy score. This resulted in five ensemble models corresponding to current climatic suitabilities and four models corresponding to future climatic suitabilities representing RCP 4.5 and 8.5 for the time periods 2050 and 2070. For the evaluation of relative importance of each climatic variable in governing the current and future distribution of the selected species, permutation procedure was used following Rather et al. (2022).

The *RangeSize* function in *biomod2* package was used to quantify and represent the range change over future climatic scenarios. From the output of the package, information about absolute metrics viz., "Loss, Absent, Stable and Gain" is obtained. Loss is calculated as the number of suitable pixels predicted to be lost under changing climatic scenarios; gain as the number of pixels that are currently unsuitable and predicted to become suitable in future, absent as the number of pixels that are neither suitable nor predicted to be suitable in future and stable as the number of pixels currently suitable and predicted to remain suitable in future. Three additional relative metrics (Percentage Loss, Percentage gain and Range change) were derived from the four absolute metrics following Rather et al. (2022) and Wani et al. (2024b).

3 Results and discussion

With committee averaging TSS and AUC values of 0.56 and 0.87 and weighted mean TSS and AUC values of 0.63 and 0.89, respectively, the final ensemble model performed well in predicting the target species' distribution. In contrast to the other algorithms used, ANN and SRE showed the lowest accuracy, while GBM, RF, MaxEnt, and GLM performed fairly well. Other algorithms like FDA, MARS, GAM, and CTA showed intermediate performances (Figure 3). Fair performance of GBM, RF, MaxEnt, and GLM in ensemble modeling approaches has also been documented in other ensemble modelling studies (Mohammady et al., 2021; Edalat et al., 2022; Wani et al., 2022b).

3.1 Variable importance

Following Pearson's correlation analysis, five variables were selected for modelling the distribution of *B. stracheyi* under current climatic conditions (Figure 4). These variables include Bio1 (Annual Mean Temperature), Bio2 (Mean Diurnal Range), Bio4 (Temperature Seasonality), Bio12 (Annual Precipitation) and Bio15 (Precipitation Seasonality). By selecting variables with lower correlation, the final dataset reflects a reduced redundancy in the environmental data, expected to lead to better model performance and more reliable ecological predictions. Reducing multicolinearity among variables is crucial for ensuring that the model predictions are not skewed by the inclusion of highly correlated predictors (Dormann et al., 2013b). Among the selected variables, distribution of *B. stracheyi* is most strongly influenced by Bio1, Bio12 and Bio2 (Table 2). Bio1 represents the average annual temperature, integrating both daily and seasonal variations. Changes in annual mean temperature can direct or indirect affect the physiology and metabolic activities, thereby impacting species distribution. Bio12, which measures total annual precipitation (in millimeters), plays a crucial role in shaping species distribution by affecting soil moisture levels and soil-plant-atmosphere-continuum (Wani et al., 2024b). Furthermore, the dependence on Bio2 suggests that regions with reduced diurnal fluctuations provide more stable environments, which are likely preferred by *B. stracheyi*. In contrast, extreme diurnal variations may increase physiological stress, potentially affecting the distribution and survival of species (Venkat and Muneer, 2022).

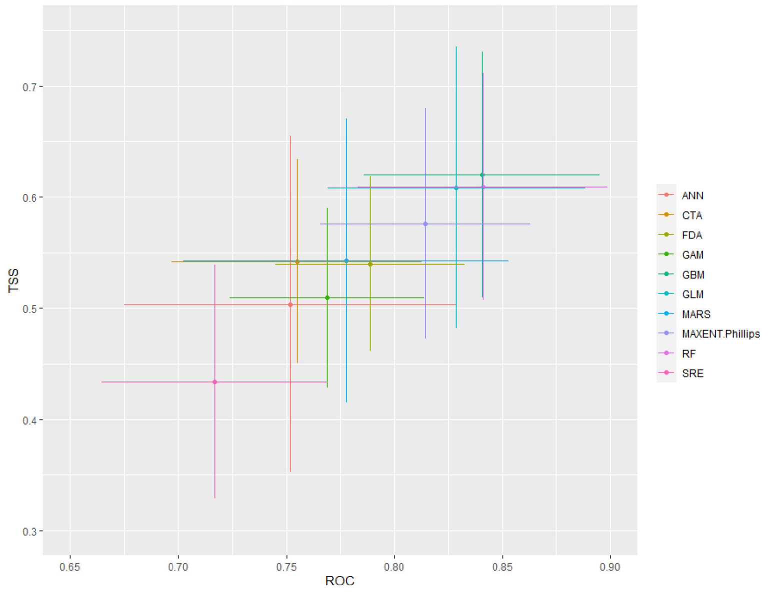

FIGURE 3
Mean algorithmic model evaluation scores for (*B*) *stracheyi* based on two distinct evaluation metrics, ROC (AUC) and TSS.

3.2 Predicted distribution and range change dynamics

Findings of the ensemble model revealed that under the current climatic conditions, ideal habitats for *B. stracheyi* spread throughout the higher elevations of Jammu and Kashmir most appropriately towards Kargil, Leh, Gilgit-Baltistan, Mirpur, Ghizar, and Rajouri-Poonch region. In Kashmir Valley, Sonamarg, Gulmarg and parts of Shopian district are predicted to be highly suitable for the plant and certain areas of Kupwara, Bandipora, Baramulla, and Ganderbal are predicted to be moderately suitable for *B. stracheyi*. Lower elevations are predicted to be unsuitable for its growth (Figure 5), supported by the fact that the targeted plant is an alpine species with its distribution reported from the higher elevations of the Himalayan region (Tiwari et al., 2017). Future ensemble model predictions indicated that, across all future climatic scenarios, the majority of the habitats that are currently suitable will continue to be so. However, the species will shift towards the north and southeast in some currently unsuitable habitats, like northern Gilgit-Baltistan, northeastern Leh, and some parts of Budgam and Baramulla (Figure 6).

Using RCP 4.5 and RCP 8.5 allows comparative assessment of how potential distribution of *B. stracheyi* may shift under contrasting climate futures. These RCP's have been extensively validated and widely used in ecological research, ensuring consistency with previous studies, and facilitating comparisons with historical trends. RCPs provide reliable insights into the

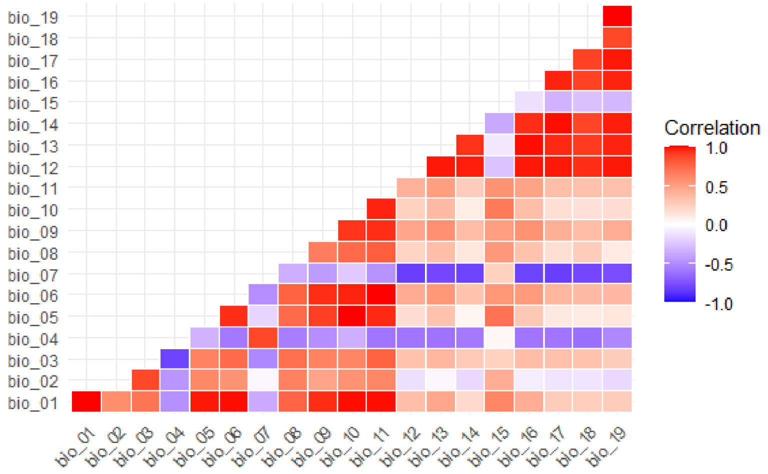

FIGURE 4
Plot showing the Pearson correlation between the 19 bioclimatic variables.

TABLE 2 **Individual and total algorithmic importance scores for the chosen bioclimatic variables.**

Biovariables	GLM	GBA	GAM	CTA	ANN	SRE	FDA	RF	MARS	MaxEnt	Mean
Bio1	0.508	0.473	0.519	0.663	0.327	0.394	0.682	0.399	0.544	0.535	0.505
Bio2	0.326	0.215	0.353	0.249	0.189	0.315	0.260	0.181	0.28	0.318	0.268
Bio4	0.003	0.074	0.186	0.041	0.086	0.178	0.143	0.192	0.091	0.043	0.104
Bio12	0.426	0.264	0.36	0.396	0.219	0.404	0.498	0.223	0.384	0.485	0.366
Bio15	0.15	0.027	0.206	0	0.065	0.227	0.091	0.140	0.020	0.054	0.098

impacts of different greenhouse gas concentration trajectories on species distribution and habitat suitability (del Río et al., 2021; Shrestha et al., 2021). The model projects a considerable increase in suitable habitats for *B. stracheyi*, particularly under more severe climate change scenarios (RCP8.5). The range change depicts a considerable increase approximately 42.57% under RCP4.5 for 2050 to as high as 57.31% under RCP8.5 for 2070, as per committee averaging. A similar trend is observed when using weighted mean calculations, with gains ranging from 41.40% to 55.86% across scenarios and timeframes (Table 3). Qiu et al. (2024) have also predicted that the suitable habitat of *B. stracheyi* is going to expand in future under SSP1-2.6 and SSP2-45.

Results from the ensemble modelling indicate that most of the currently suitable habitats for *B. stracheyi* are projected to remain suitable in future, as represented by the purple patches in Figure 7. This stability is particularly significant for conservation planning, as it suggests that protecting these areas could maintain the species core populations, despite ongoing climatic changes. The persistence of current habitats could be attributed to the adaptability of *B. stracheyi* across a range of climatic conditions, as well as the relative stability of these regions under future scenarios. These findings suggest that *B. stracheyi* has the potential to exploit emerging ecological niches that are expected to become more favorable due to shifts in temperature and precipitation patterns driven by climate change. *B. stracheyi* exhibits lithotriptic property meaning it has the ability to break stones, which serves as an adaptative advantage, allowing it to thrive in environments that are often unsuitable for other plant species (Kumar and Tyagi, 2013). Additionally, its

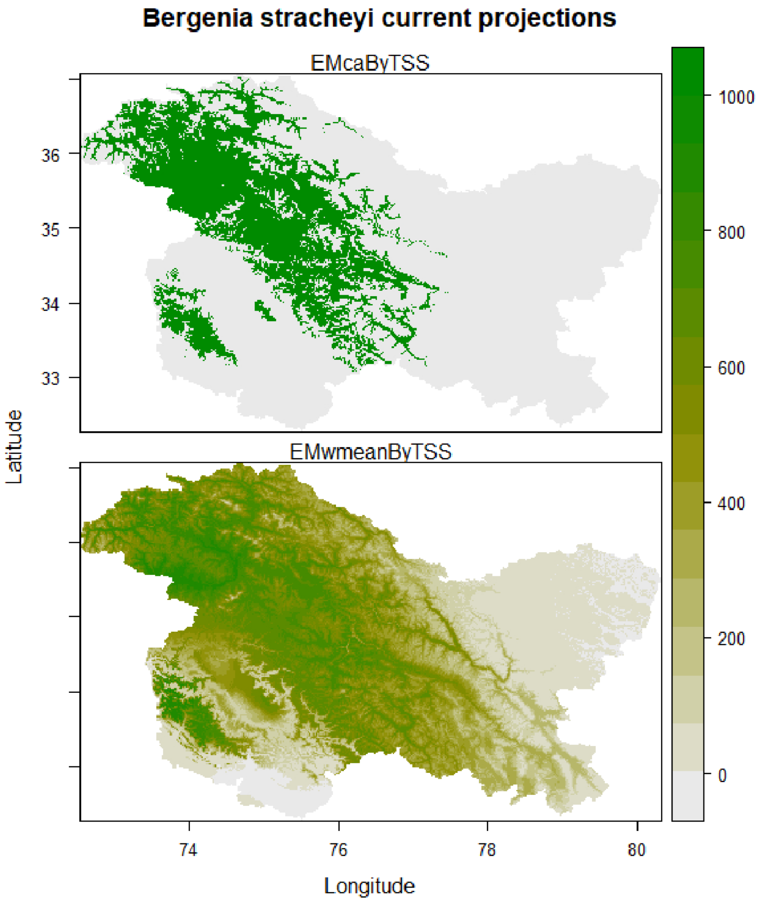

FIGURE 5
Predicted distribution of (*B*) *stracheyi* under present climatic conditions.

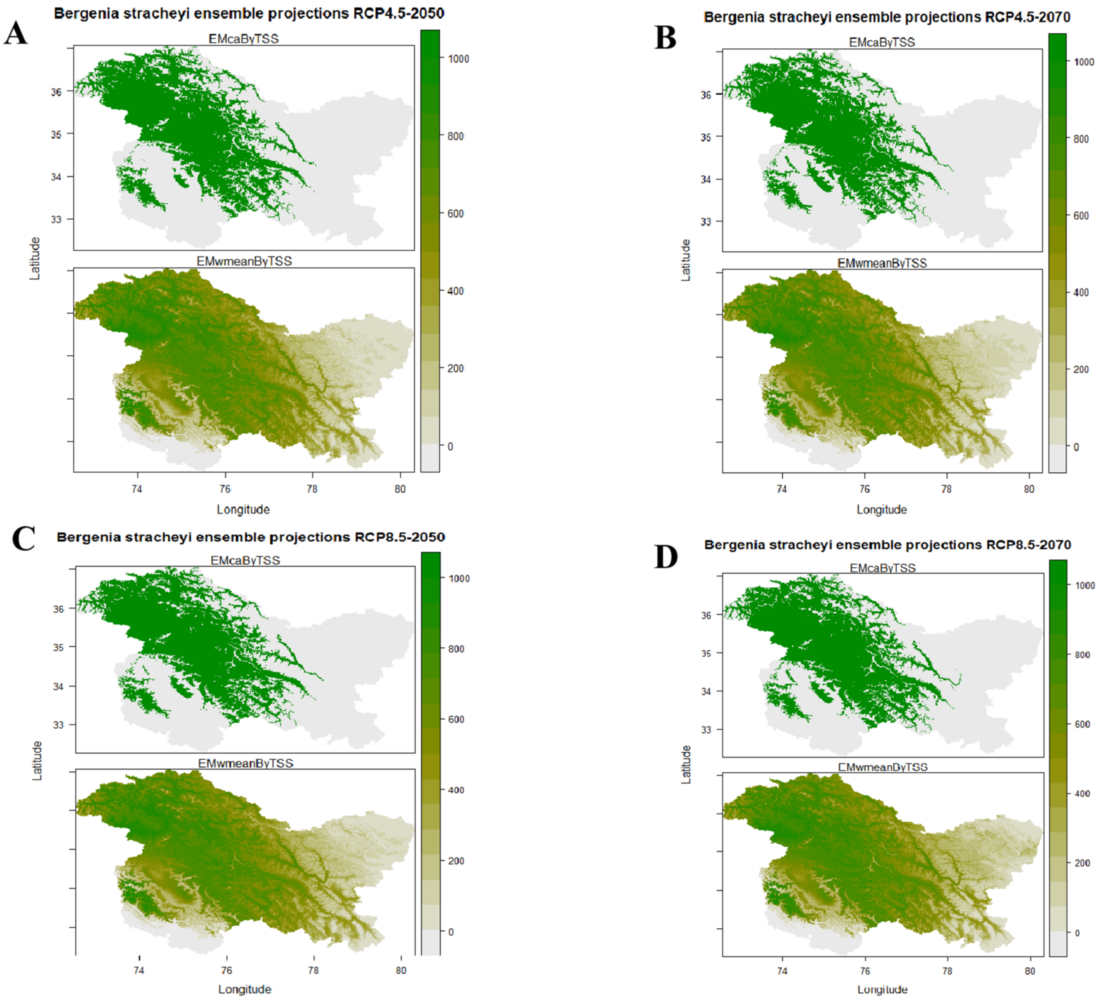

FIGURE 6
Predicted future distribution of (*B*) *stracheyi* under **(A)** RCP 4.5 (2050); **(B)** RCP 4.5 (2070); **(C)** RCP 8.5 (2050) and **(D)** RCP 8.5 (2070).

unique morphology characterized by thick and fleshy leaves, enables efficient nutrient and water storage, helping the plant withstand harsh alpine conditions (Pandey et al., 2017).

Some areas currently deemed unsuitable for *B. stracheyi* are projected to become suitable in the future, indicated by yellow patches in Figure 6. These regions are primarily located in northern Gilgit-Baltistan, northeastern Leh, and parts of Budgam and Baramulla. The species is predicted to shift its distribution northward and southeastward, aligning with findings from Qiu et al. (2024), who reported that two Himalayan species of *Bergenia*, *B. ciliata* and *B. stracheyi* are expected to expand their ranges in similar directions. The areas predicted to become suitable for *B. stracheyi* in the future are expected to experience climatic conditions that align with its ecological requirements. This

TABLE 3 Range shift statistics for *B. stracheyi* under future climate change scenarios in comparison to the current climate conditions (the values are given in km^2).

Scenario	Ensemble type	Loss	Absent	Stable	Gain	Loss%	Gain%	Range change%
RCP4.5 (2050)	Committee Averaging	426.5	139,784	56,413	24,623	0.751	43.321	42.571
RCP4.5 (2070)	Committee Averaging	710.7	138,621	56,129	25,786	1.250	45.374	44.124
RCP8.5 (2050)	Committee Averaging	297.4	134,779	56,442	26,629	0.700	52.127	51.427
RCP8.5 (2070)	Committee Averaging	549	131,280	56,058	33,358	1.375	58.687	57.312
RCP4.5 (2050)	Weighted Mean	442.1	138,358	57,863	24,583	0.758	42.164	41.405
RCP4.5 (2070)	Weighted Mean	722.6	137,118	57,583	25,824	1.239	44.292	43.052
RCP8.5 (2050)	Weighted Mean	418.9	133,349	57,887	29,593	0.719	50.755	50.037
RCP8.5 (2070)	Weighted Mean	790.1	129,580	57,515	33,362	1.355	57.219	55.864

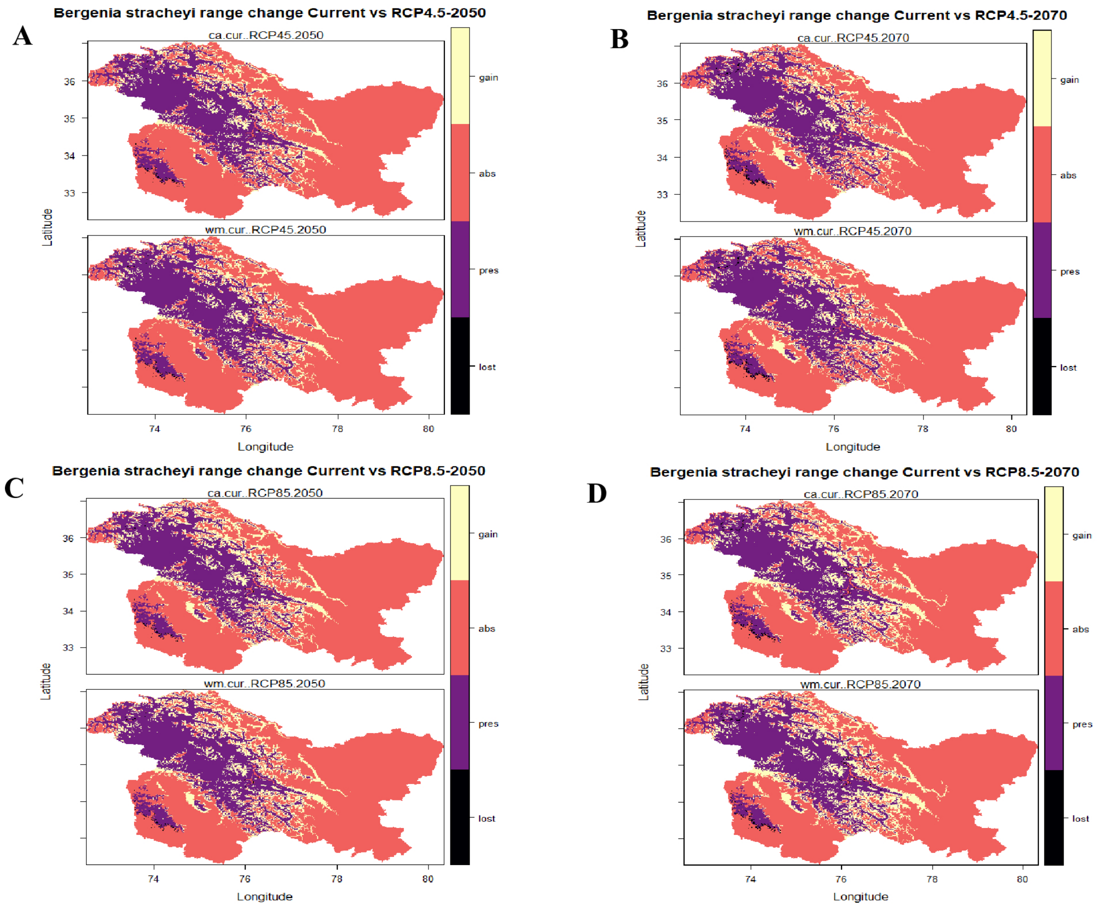

FIGURE 7
Range change dynamics showing the loss, gain, absent and presence under future climatic scenarios **(A)** RCP 4.5 (2050); **(B)** RCP 4.5 (2070); **(C)** RCP 8.5 (2050); and **(D)** RCP 8.5 (2070).

expansion may contribute to an overall increase in population size and genetic diversity, providing an opportunity for adaptive resilience under changing climatic conditions. However, despite the projected habitat gains, some areas currently identified as suitable, including parts of Rajouri-Poonch and Mirpur (Pakistan), are expected to become unsuitable in the future (black patches in Figure 7). These habitat losses are likely driven by climatic shifts that exceed the tolerance range of *B. stracheyi*.

Climate change is profoundly reshaping plant species distributions worldwide, with significant consequences for ecosystems, biodiversity, and human societies (Kelly and Goulden, 2008; Pecl et al., 2017; Mosoh et al., 2024). Rising temperatures, changing precipitation patterns, and more frequent extreme weather events are forcing many plant species to shift their ranges to higher latitudes or elevations in search of suitable habitats (Muluneh, 2021; Yang et al., 2024; Zhao et al., 2024). With rising temperatures, *B. stracheyi* is predicted to expand its distribution northward and southeastward. Similar range shifts have been predicted for other plant species in the Himalayan region (Telwala et al., 2013; Manish et al., 2016; He et al., 2019; Manish, 2022; Wani et al., 2022a; Qiu et al., 2024; Satish et al., 2024). Such shifts in plant distribution have far-reaching consequences for ecosystem functioning and stability and the services these species provide to human communities. Additionally, these shifts may disrupt plant-pollinator interactions, leading to phenological mismatches with potentially severe ecological consequences (Karthik et al., 2021; Shivanna, 2022). As climate change disrupts the timing of phenological events, plants may flower before their pollinators become active or vice versa, potentially leading to reproductive failures and population declines. The predicted range shifts in the distribution of *B. stracheyi* underscore the urgency of implementing local conservation measures to mitigate the impacts of climate change.

4 Limitations of the study

Although this study employs a robust methodology and well performing models, certain limitations exist. The distribution of *B. stracheyi* was primarily modeled using nineteen bioclimatic variables, which may have led to an overestimation of actual range. Incorporating additional variables such as topographical, soil features, land-use, and biotic interactions could further refine the model and provide a comprehensive understanding of the species distribution (Qiu et al., 2024). Furthermore, the future climatic projections in this study were based on CMIP5 (IPCC AR5) which is now considered obsolete. The latest CMIP6 framework introduces updated climate scenarios known as Shared Socioeconomic Pathways (SSPs), developed by the energy modelling community, offering more refined and policy relevant climate projections.

5 Conclusion

B. stracheyi is an important medicinal plant native to the Himalayas, occurring at elevations between 3300 and 4800 m asl. In the present study, an ensemble modelling approach was used to predict the current and future distribution of *B. stracheyi* under the anticipated climate change scenarios for the time periods 2050 and 2070. The findings of the study revealed that the distribution of *B. stracheyi* is predominantly determined by temperature and precipitation variables impeding that alterations in temperature and precipitation can have a considerable direct or indirect effect on the plant, affecting its distribution. Results of the ensemble modelling revealed that most of the currently suitable habitats for *B. stracheyi* are likely to remain suitable in future. Some currently unsuitable areas for the plant are expected to become suitable in future, allowing the species to expand its distribution northward and southeastward. Further, some currently areas are predicted to become unsuitable for the plant in future. Thus, overall *B. stracheyi* is predicted to show major range change shifts under future climatic scenarios. Findings of the present study endorse and lay a reliable foundation for conservation planning of *B. stracheyi*. Further, present study recommends that distribution of *B. stracheyi* should be predicted using the latest future climatic scenarios and all possible biotic and abiotic variables for better model predictions.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

ZW: Data curation, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. JD: Data curation, Supervision, Validation, Visualization, Writing – review & editing. AL: Writing – review & editing. SP: Conceptualization, Methodology, Supervision, Visualization, Writing – review & editing. SS: Funding acquisition, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

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