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Modeling Forest Biodiversity under Climate Change: A MaxEnt Case Study of *Cedrus Deodara* in Khyber Pakhtunkhwa, Pakistan

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Abstract

This study models the current and future distribution of *Cedrus Deodara*, a native conifer of Khyber Pakhtunkhwa (KP), Pakistan, at a spatial resolution of 1 km. Presence-only occurrence data were obtained from the Global Biodiversity Information Facility (GBIF) and combined with bioclimatic and topographic variables. To reduce redundancy, a multicollinearity test was performed on 22 candidate predictors, and highly correlated variables ($r \geq 0.9$) were excluded. The Maximum Entropy (MaxEnt) model was applied to predict species distribution under present conditions and two future climate scenarios (SSP2-4.5 and SSP5-8.5) for 2090. Model performance was evaluated using the AUC, TSS, and overall accuracy. The obtained results show a good performance of the model for present and future models as well, gaining the ROC-AUC value of 0.72 and 0.77, respectively. Based on the 10^{th} percentile training presence-threshold dependent, the overall accuracy of the model and TSS are 0.75 and 0.74, respectively. Jackknife analysis revealed precipitation variables as the most influential contributors to *Cedrus Deodara* distribution. Results suggest that the species will experience substantial habitat contraction under SSP2-4.5, whereas distributional shifts under SSP5-8.5 are comparatively minor. These findings emphasize the vulnerability of *Cedrus Deodara* to climate change and demonstrate the value of MaxEnt modeling for informing conservation and management strategies in biodiversity-rich regions.

Keywords: Global Biodiversity Information Facility (GBIF); MaxEnt; Species Distribution; Habitat Conservation; Biodiversity

1. Introduction

An ecosystem is a dynamic community of organisms (plants, animals, and microorganisms) that interact with one another and with their physical environment, including air, water, and soil (Tsujimoto et al., 2018). These interactions sustain essential processes such as energy flow, nutrient cycling, and ecological stability (Gillani et al., 2025; Guillaumot et al., 2019). Beyond trophic relationships, species engage in symbiotic interactions (Rahman et al., 2022): mutualism, where both species benefit (e.g., bees pollinating flowers); commensalism, where one benefits without affecting the other (e.g., birds nesting in trees); and parasitism, where one benefits at the expense of the host (e.g., ticks feeding on mammals) (Liu, 2016). Such intricate relationships underscore the importance of biodiversity, as alterations in one species can cascade through the ecosystem, affecting its resilience and functionality (Verma, 2018; Waheed et al., 2023). Species distribution is shaped by a combination of environmental, biological, and anthropogenic factors. Abiotic conditions such as temperature, precipitation, and climate strongly influence habitat suitability, while soil texture, nutrient availability, and pH further affect species persistence (Ali et al., 2023; Asad et al., 2024; Rahman et al., 2022, 2024). Topographic features, including slope, aspect, and elevation, modify local microclimates, and water availability is often a critical determinant for both terrestrial and aquatic species (Ali et al., 2023; Asad et al., 2024; Ashcroft et al., 2011; Khan et al., 2021). Human activities such as urbanization, deforestation, and agriculture fragment habitats, while climate change and pollution alter ecosystems on broader scales, driving species migration or shifts in habitat suitability (Malik et al., 2020; Ahmad et al., 2024; Asad et al., 2024; Khan et al., 2021; Reese et al., 2005; Tayyab et al., 2023).

Climate change may also facilitate environmental degradation (Shah et al., 2019) and the spread of invasive species, further threatening native biodiversity. In addition, evolutionary adaptations, historical processes, and natural barriers such as mountains or rivers can constrain species' ranges. Collectively, these factors create a complex network of interactions that define ecosystems and shape relationships among different trophic levels (Ali et al., 2023, 2024; Arshad et al., 2022; Thibaud et al., 2014).

Khyber Pakhtunkhwa (KP), the northwestern province of Pakistan, is characterized by diverse topography that ranges from dense forests and high mountains to arid valleys and fertile plains. This environmental heterogeneity, coupled with climatic variation, makes KP a biodiversity hotspot. Coniferous forests dominate much of the region, particularly in higher elevations of Swat, Chitral, and Dir, where species such as *Cedrus Deodara*, spruce, and pine are abundant. These forests play a vital role in carbon storage, hydrological regulation, and habitat provision, while also supporting the livelihoods of local communities in mountainous areas. However, rapid urbanization, deforestation, and climate change threaten these ecosystems, highlighting the urgent need for effective conservation and ecological management. Predictive modeling approaches can provide valuable insights into how climate change may alter species distributions and habitat suitability (Ali et al., 2020; Durrani et al., 2024; Khan et al., 2019, 2021).

Species distribution models (SDMs) are widely used to address conservation, ecological, and biogeographical questions (Ali et al., 2014; Kunwar et al., 2023). Different SDM techniques are available (Guisan and Thuiller, 2005), some of which use "presence only data" and others use "presence-absence data" (Ali et al., 2023; Ali et al., 2014; Kharel et al., 2024; Lobo et al., 2010). SDMs are particularly valuable for identifying threatened species, assessing the impacts of climate change, and evaluating habitat suitability (Malla et al., 2023; Ranjitkar et al., 2014). Machine learning algorithms, including MaxEnt, Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN), improve the classification techniques (Hassan et al., 2025). Among various machine learning techniques, Maximum Entropy (MaxEnt) modeling has emerged as one of the most widely applied techniques. MaxEnt combines species occurrence records with environmental variables to predict current and future distributions, making it especially useful in conservation planning under climate change scenarios (Khan et al., 2021).

MaxEnt is particularly effective when species occurrence data are available, as it performs well with presence-only records (Khan et al., 2021). The model integrates species presence data with environmental and topographic predictors to estimate habitat suitability. Owing to its flexibility and strong predictive performance, MaxEnt has become widely used in ecology, climate change research, and conservation planning, especially for predicting range shifts and identifying suitable habitats under future climate scenarios (Javidan et al., 2021).

In this study, we focus on *Cedrus Deodara* (Deodar cedar), an evergreen conifer native to the western Himalayas. Renowned for its height, majestic form, and ecological importance, *Cedrus Deodara* also holds cultural and spiritual significance. The name "Deodara" is derived from Sanskrit, meaning "wood of the gods," reflecting its historical importance in the Indian subcontinent (Chaudhary et al., 2011; Gillani et al., 2025). *Cedrus Deodara* typically occurs at elevations between 1,500 and 3,200 meters, where it thrives under cool climatic conditions (Sharma et al., 2018). Ecologically, it plays a vital role in stabilizing soils, preventing erosion, regulating microclimates, and providing habitat for associated species. It often coexists with oak, rhododendron, and pine in montane forests of the western Himalayas (Pandey et al., 2023). As per the literature review, most of the studies on species distribution modeling have been conducted on the district level, except for Durrani et al. (2024), who conducted the study on the provincial level. Keeping this background in mind, the overall objective of this study is to integrate bioclimatic and topographic variables with species occurrence data to model the current and future distribution of *Cedrus Deodara* at the provincial level in Khyber Pakhtunkhwa using MaxEnt. Two Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5) were employed to project distribution shifts by 2090.

2. Study Area

The study was conducted in Khyber Pakhtunkhwa (KP), the northwestern province of Pakistan, formerly known as the North-West Frontier Province (NWFP) (Fig. 1). KP covers an area of approximately 74,521 km² and shares borders with Punjab to the southeast, Afghanistan to the north and west, and Baluchistan to the southwest. The province is characterized by diverse topography, ranging from high mountain ranges to fertile plains, and exhibits substantial climatic variability. This environmental heterogeneity has created multiple ecological zones, making KP a recognized biodiversity hotspot in Pakistan (Majid et al., 2023).

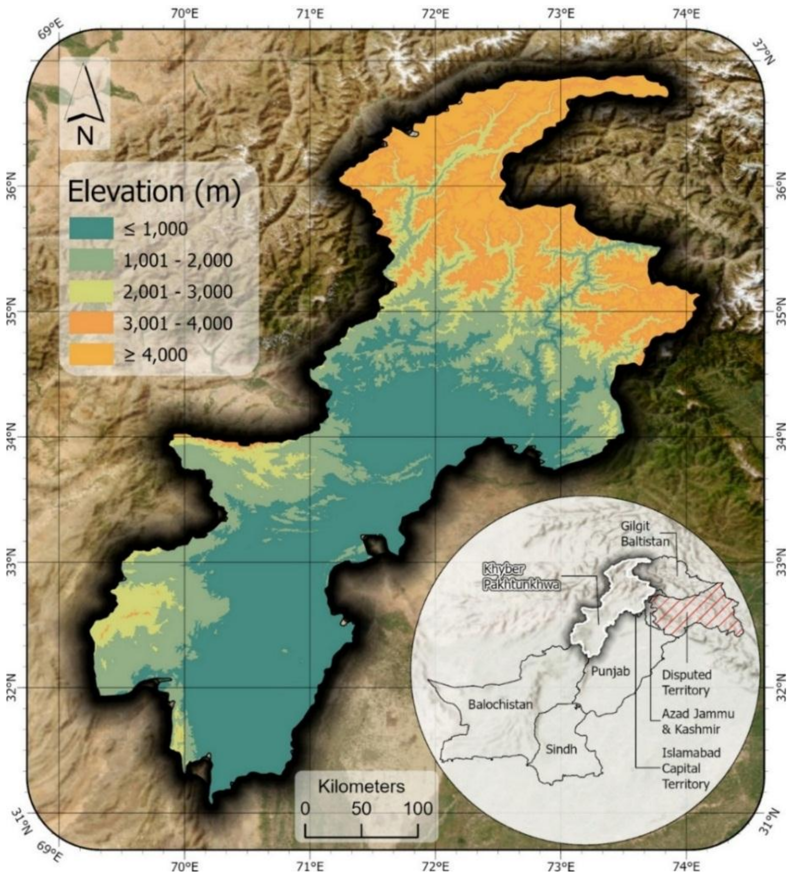

Fig. 1. Map of the study area in Khyber Pakhtunkhwa (KP), Pakistan, showing provincial boundaries and its geographical location within the country.

3. Methodology

The methodological framework adopted in this study is illustrated in Figure 2. It summarizes the sequential stages followed, including data acquisition, preprocessing, modeling, evaluation, and map generation of the *Cedrus Deodara* distribution.

3.1. Input Data

3.1.1. Bioclimatic Variables

Nineteen bioclimatic variables (Bio1–Bio19) were obtained from the WorldClim database (www.worldclim.org) at a spatial resolution of ~1 km (30 arc-seconds). These variables capture long-term climatic patterns, particularly temperature and precipitation, which are known to be strongly related to the species distributions (Ray et al., 2011). The full list of variables and their descriptions is provided in Table 1.

3.1.2. Topographic Variables

Three topographic predictors, including slope, aspect, and Terrain Roughness Index (TRI), were derived from the ASTER Global Digital Elevation Model (GDEM v3), downloaded from NASA's Earth Data portal. These variables account for microclimatic variation caused by terrain features.

3.1.3. *Species Occurrence Data*

Presence-only occurrence records of *Cedrus Deodara* were retrieved from the Global Biodiversity Information Facility (GBIF; https://www.gbif.org/). Duplicate and erroneous records were removed to minimize spatial bias and ensure model reliability. To address the biases that could affect the model performance, spatial filtering of ~1km x 1 km (Malla et al., 2023) was applied using the "spThin" package (Khanal et al., 2022; Kharel et al., 2024) in R (R Core Team, 2025, version: 4.4.2) to reduce the spatial autocorrelation.

3.2. Data Processing

All environmental variables were standardized to a spatial resolution of 1 km and clipped to the administrative boundary of Khyber Pakhtunkhwa (KP). Raster snapping was performed to ensure alignment across datasets.

To address multicollinearity among the predictors, a Pearson correlation analysis was performed using the programming language R. Variables with correlation coefficients $r \geq 0.9$ were excluded from subsequent modeling. The selected variables were converted into ASCII format for compatibility with the MaxEnt software.

3.3. Species Distribution Modeling

Species distribution modeling was performed using the Maximum Entropy algorithm (MaxEnt; Phillips et al., 2006), which is particularly suited for presence-only data. Both current and future distributions were modeled. Future projections were generated using the BCC-CSM2-HR Global Circulation Model under two Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5) for the period 2081–2100 (hereafter 2090). Previously, these data have been used in Pakistan (Gilani et al., 2020), the South Asian region (Khan et al., 2022), and in the Hindu Kush-Himalaya (HKH) region (Malik et al., 2022) with good accuracy for the species distribution with respect to climate change.

3.4. Model Evaluation

Model performance was evaluated using multiple statistical measures. The Area Under the Curve (AUC) of the Receiver Operating Characteristics (ROC) was employed to assess the model's ability to discriminate between suitable and unsuitable habitats. In addition, the True Skill Statistic (TSS) was calculated to provide a balanced measure of sensitivity and specificity. Furthermore, the Jackknife test was conducted to determine the relative importance and contribution of each environmental variable to the model's predictive performance.

3.5. Mapping and Visualization

Final habitat suitability maps were generated in the ArcGIS software suite. Suitability was expressed as a continuous probability surface, categorized into classes ranging from very low to very high. Maps were produced for the current distribution as well as for future climate change scenarios (SSP2-4.5 and SSP5-8.5) to visualize potential shifts in the distribution of *Cedrus deodara*.

4. Results and Discussion

4.1. Variable Selection

The multicollinearity test reduced the initial set of 22 variables (19 bioclimatic and 3 topographic) to 11 predictors, including eight bioclimatic and three topographic variables. Variables with Pearson correlation coefficients ($r \geq 0.9$), such as Bio2, Bio3, Bio5, Bio6, Bio10, Bio11, Bio12, Bio13, Bio16, Bio18, and Bio19, were excluded from further analysis (Supplementary Table S1). This selection ensured that highly correlated predictors did not bias model performance, a practice consistent with earlier studies (Gilani et al., 2020).

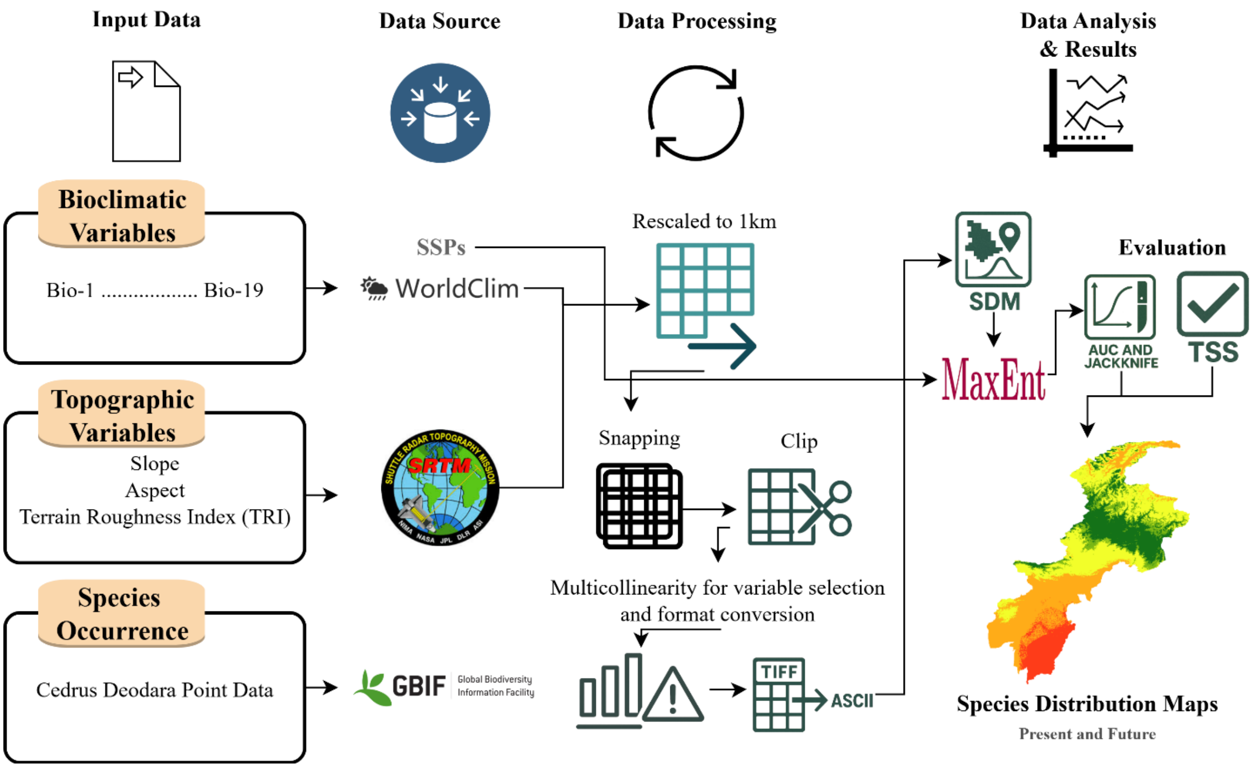

Fig. 2. Overview of the methodological framework applied for predicting the current and future distribution of *Cedrus Deodara* in Khyber Pakhtunkhwa, Pakistan.

Table 1: Nineteen bioclimatic variables (Bio1–Bio19) from WorldClim (~1 km resolution), used as predictors in MaxEnt modeling.

No	Bioclimatic Variable	Description
1	Bio-1	Annual mean temperature
2	Bio-2	Mean diurnal range (mean of monthly (max temp-min temp)
3	Bio-3	Isothermality
4	Bio-4	Temperature seasonality
5	Bio-5	Max temperature of the warmest month
6	Bio-6	Minimum temperature of the coldest month
7	Bio-7	Temperature annual range (bio-5 – bio-6)
8	Bio-8	Mean temperature of the wettest quarter
9	Bio-9	Mean temperature of driest quarter
10	Bio-10	Mean temperature of the warmest quarter
11	Bio-11	Mean temperature of the wettest quarter
12	Bio-12	Mean temperature of the coldest quarter
13	Bio-13	Annual precipitation
14	Bio-14	Precipitation of the wettest month
15	Bio-15	Precipitation of the driest month
16	Bio-16	Precipitation seasonality (coefficient of variation)
17	Bio-17	Precipitation of the driest month
18	Bio-18	Precipitation of the warmest month
19	Bio-19	Precipitation of the coldest month

4.2. Model Performance

The MaxEnt model demonstrated reliable predictive power, with training AUC values above 0.80 across all scenarios (Table 2). The test AUC values were slightly lower, ranging from 0.69 for the current period to 0.78 under SSP2-4.5 and 0.73 under SSP5-8.5. These results indicate good model performance, although the lower test AUC for the current period suggests moderate predictive strength, possibly due to limited presence data or environmental variability not captured in the predictors. Nonetheless, the consistency between training and test values indicates the model was not overfit.

Table 2: Training and test AUC values of the MaxEnt model for current and future climate scenarios (SSP2-4.5 and SSP5-8.5) predicting the distribution of *Cedrus Deodara*.

Scenario	Training AUC	Test AUC
Current	0.80	0.69
SSP2-4.5	0.86	0.78
SSP5-8.5	0.84	0.73`

4.3. Variable Contribution

The Jackknife test revealed that precipitation-related variables were the dominant predictors of *Cedrus Deodara* distribution (Fig. 3). Specifically, precipitation of the wettest month (Bio14) and precipitation of the driest month (Bio17) contributed most strongly to the model. These findings highlight the ecological importance of water availability for *Cedrus Deodara*, which thrives in montane environments where precipitation plays a crucial role in maintaining soil moisture and regulating microclimate. Similar patterns have been reported in other coniferous species of the Western Himalayas (Pandey et al., 2023).

4.4. Model Accuracy and Validation

Evaluation metrics further confirmed the robustness of the model. The TSS values exceeded 0.70 across all scenarios, while Cohen's Kappa ranged between 0.61 and 0.65, and overall accuracy surpassed 70% (Table 3). Sensitivity and specificity values were balanced, demonstrating that the model was equally effective in identifying suitable and unsuitable habitats. These results align with the thresholds suggested by Allouche et al. (2006), which consider TSS values above 0.6 as indicative of useful predictive accuracy.

4.5. Spatial Distribution Patterns

The suitability maps indicate a clear elevational and latitudinal gradient for *Cedrus Deodara*, as shown in Figure 4. By following the criteria used by Gilani et al. (2020), Paudel et al. (2025), and Yang et al. (2013), we renamed the classes of habitat suitability distribution as: 1) Very Low (0-0.2), 2) Low (0.2-0.4), 3) Moderate (0.4-0.6), 4) High (0.6-0.7), and 5) Very High (0.7-1.0). Under current climate, high to very high suitability forms a continuous belt across the northern mountain districts of KP, most prominently the Hindu Kush, western Himalayan zone (e.g., Chitral, Upper/Lower Dir, Swat, Kohistan, and parts of Mansehra/Hazara), while the central lowlands show medium suitability and the southern arid plains (e.g., Karak, Bannu, Dera Ismail Khan) remain largely low to very low. Under SSP2-4.5 (2090), this high-suitability belt becomes noticeably fragmented: mid-elevation areas transition from green to yellow/orange, and marginal zones in the central province lose suitability, suggesting an upslope and northward contraction. In contrast, the SSP2-8.5 (2090) projection retains much of the northern core, with extensive high/ very-high suitability persisting and only localized edge losses; some northeastern highlands appear to maintain or slightly consolidate suitability relative to SSP2-4.5. Overall, the maps point to range reorganization along the montane belt, with the strongest contraction under SSP2-4.5 and comparatively smaller net losses under SSP2-8.5, implying an upward/northward shift in suitable habitat and emphasizing the role of mountain microclimates in buffering *Cedrus Deodara* populations. Beyond the system-based evaluation (AUC, TSS, and Kappa), the ecological significance of our climate change scenarios is strongly supported by the literature published on the same study area. Under SSP 5-8.5, the predicted northward shift of Cedrus Deodara is supported by the findings of Durrani et al. (2024) in the same geographical extent on eight tree species of KP, including *Cedrus Deodara*. Both validations (system-based and external) provide the robustness of the predictive model. It confirms the latitudinal shift of species within the Hindu Kush Himalayan (HKH) region under different climate change scenarios.

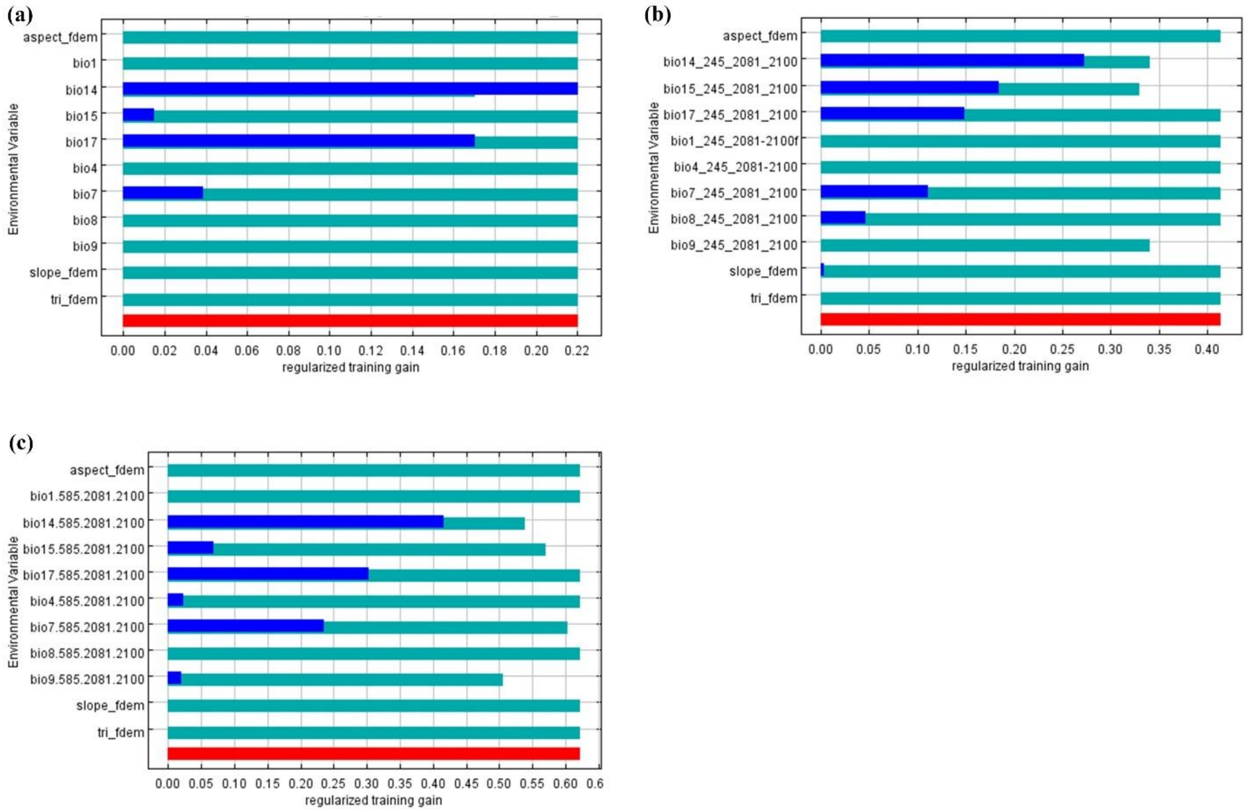

Fig. 3. Jackknife test results showing the relative importance of environmental variables in predicting the distribution of *Cedrus Deodara* for **(a)** current and future climate scenarios, **(b)** SSP2-4.5, and **(c)** SSP2-8.5 for 2090.

Table 3: MaxEnt model evaluation metrics for *Cedrus Deodara*.

Scenario	ROC-AUC	TSS	Max Kappa	Overall Accuracy	Sensitivity	Specificity
Current	0.72	0.71	0.61	0.72	0.64	0.72
SSP2-4.5	0.80	0.79	0.65	0.80	0.69	0.80
SSP5-8.5	0.74	0.74	0.63	0.74	0.72	0.74

4.6. Spatial Distribution Patterns

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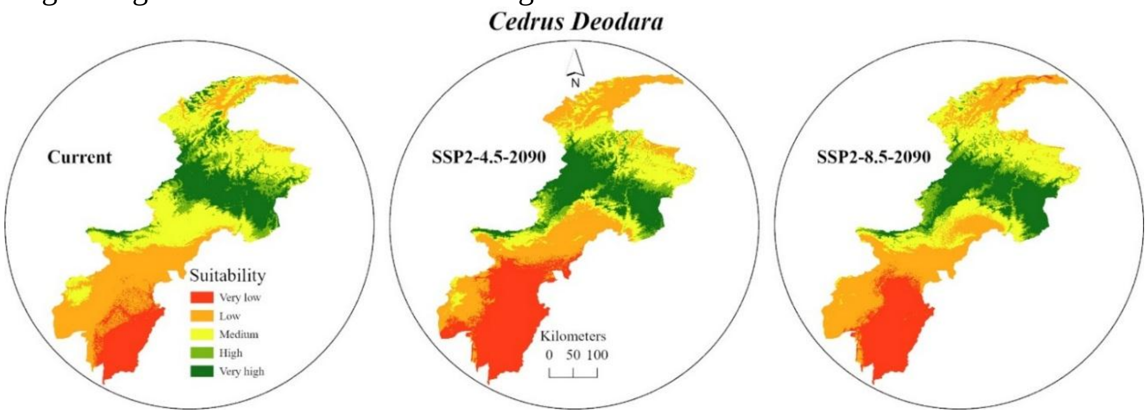

Fig. 4. Predicted habitat suitability of *Cedrus Deodara* in Khyber Pakhtunkhwa, Pakistan, under **(a)** current climate and future scenarios, **(b)** SSP2-4.5, and **(c)** SSP2-8.5 for 2090.

4.7. Implications for Conservation

The results underscore the vulnerability of *C. deodara* to climate change and highlight the need for proactive conservation measures. Regions projected to remain suitable under both scenarios may serve as climate refugia and should be prioritized for conservation. Predictive modeling approaches, such as MaxEnt, provide valuable insights for identifying critical habitats, guiding forest management, and developing strategies to mitigate biodiversity loss in the Western Himalayas.

5. Conclusion

This study applied MaxEnt species distribution modeling to assess the current and future habitat suitability of *Cedrus Deodara* in Khyber Pakhtunkhwa, Pakistan. By integrating bioclimatic and topographic variables with species occurrence records, we generated spatial predictions under present conditions and two future climate scenarios (SSP2-4.5 and SSP5-8.5) for 2090. The results demonstrate that precipitation-related variables, particularly during the wettest and driest months, are the most influential drivers of *Cedrus Deodara* distribution. Model evaluation metrics (AUC, TSS, Kappa) confirmed strong predictive performance, providing confidence in the projections.

The spatial analysis revealed that *Cedrus Deodara* currently occupies high-altitude northern regions of KP, while future climate change is expected to shift its range upward and northward. Notably, SSP2-4.5 indicates a more pronounced contraction of suitable habitat compared to SSP5-8.5, highlighting the species' sensitivity to moderate warming scenarios. These findings underscore the vulnerability of *Cedrus Deodara* to climate change and the potential loss of critical habitats if adaptive management strategies are not implemented.

Overall, this study emphasizes the value of predictive modeling in guiding conservation planning and forest management. Identifying potential refugia and high-suitability zones can support targeted conservation interventions, assist policymakers in prioritizing biodiversity hotspots, and contribute to sustainable forest management in the Hindukush Himalaya region. Future research should expand upon this approach by incorporating presence-absence data, comparing alternative modeling algorithms, and integrating additional environmental predictors such as soil and remote-sensing variables to further refine species distribution forecasts.

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Author's Contribution

Sadaf Safdar led the study by proposing the core idea, collecting and curating datasets, conducting formal analyses, producing all visual outputs, and writing the first version of the manuscript. Adeel Ahmad provided supervision, guided the overall direction of the study, and contributed to the critical review and refinement of the revised manuscript.

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Data availability

The datasets used and/or analyzed during the study are available on request from the corresponding author.

DECLARATIONS

Conflict of interest: The authors declare no competing interests.

Ethics approval and consent to participate.

The authors declare that they followed the ethics in scientific research.

Consent for publication.

Not applicable

Competing interests

The authors declare no competing interests.

Conflict of interests: The authors reported no potential conflict of interest.

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Supplementary Material

Table S1. Pearson correlation matrix among bioclimatic variables (Bio1–Bio19) and topographic factors (Aspect, Slope, and TRI). High correlation coefficients (> 0.9) indicate strong multicollinearity among several temperature- and precipitation-related predictors.

	Bio1	Bio2	Bio3	Bio4	Bio5	Bio6	Bio7	Bio8	Bio9	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19	Aspect	Slope	TRI
Bio1																						
Bio2	**0.9**																					
Bio3	**0.93**	0.82																				
Bio4	0.47	0.15	0.62																			
Bio5	**0.98**	**0.96**	0.86	0.27																		
Bio6	**0.98**	0.83	**0.95**	0.54	**0.93**																	
Bio7	0.32	0.64	0.08	0.56	0.51	0.17																
Bio8	0.78	0.61	0.71	0.68	0.7	0.76	0.1															
Bio9	0.74	0.69	0.67	0.13	0.78	0.77	0.31	0.36														
Bio10	**0.99**	**0.93**	0.9	0.34	**0.99**	**0.97**	0.41	0.71	0.78													
Bio11	1	0.88	**0.95**	0.54	**0.96**	**0.99**	0.25	0.8	0.73	**0.98**												
Bio12	0.53	0.31	0.65	**-0.9**	0.37	0.55	0.32	0.79	0.09	0.41	0.58											
Bio13	0.65	0.52	0.71	-0.8	0.55	0.64	0.03	0.81	0.29	0.55	0.69	**0.91**										
Bio14	0.36	0.2	0.62	0.62	0.23	0.45	0.45	0.36	0.24	0.31	0.41	0.68	0.54									
Bio15	0.63	0.66	0.49	0.25	0.67	0.57	0.48	0.55	0.69	0.62	0.63	0.28	0.62	-0.05								
Bio16	0.66	0.52	0.72	0.82	0.55	0.65	0.06	0.8	0.3	0.56	0.7	**0.91**	1	0.53	0.61							
Bio17	0.31	0.07	0.54	0.81	0.12	0.38	0.58	0.52	0.07	0.21	0.37	0.87	0.63	0.87	-0.15	0.63						
Bio18	0.47	0.31	0.5	0.79	0.35	0.45	0.11	0.83	0.04	0.36	0.51	**0.93**	**0.91**	0.4	0.39	**0.9**	0.67					
Bio19	0.64	0.44	0.8	0.82	0.5	0.69	0.29	0.72	0.31	0.56	0.69	**0.92**	0.81	0.85	0.23	0.81	**0.9**	0.73				
Aspect	0.59	0.41	0.56	0.61	0.48	0.57	0.05	0.75	0.13	0.52	0.61	0.71	0.61	0.34	0.21	0.6	0.59	0.68	0.69			
Slope	0.48	0.59	0.41	0.15	0.53	-0.4	-0.5	0.53	0.41	-0.48	-0.48	-0.39	-0.57	-0.14	-0.66	-0.54	-0.11	-0.46	-0.41	-0.56		
TRI	0.71	0.59	0.69	0.34	0.66	0.71	-0.1	0.63	0.46	-0.72	-0.71	-0.46	-0.35	-0.48	-0.11	-0.34	-0.49	-0.3	-0.67	-0.58	0.27	