Pak. J. Bot., 59(4): April 2027.

ARTICLE | DOI: http://dx.doi.org/10.30848/PJB2027-4(10)

TOPO-CLIMATIC DETERMINANTS OF *CEDRUS DEODARA* HABITAT SUITABILITY UNDER FUTURE CLIMATE EXTREMES IN NORTHERN PAKISTAN

RAJA WAQAR AHMED KHAN[1], RAJA WAJEEHA AFZAL KHAN[1], HAMAYUN SHAHEEN[1], MUHAMMAD EJAZ UL ISLAM DAR[1*] AND TARIQ SAIFF ULLAH[2]

[1]Department of Botany, The University of Azad Jammu and Kashmir, King Abdullah Campus, Muzaffarabad, AJK 13101. Pakistan
[2]Department of Botany, University of Kotli, Azad Jammu and Kashmir, Kotli, AJK. 11100, Pakistan

*Corresponding author's email: ejazdar1@gmail.com

Abstract

Species distribution in mountain ecosystems is strongly influenced by environmental conditions. In northern Pakistan, changes in climate are increasingly affecting forest habitats. Although climatic factors are widely studied, the role of topography and hydrological conditions in shaping habitat suitability remains poorly understood. This study utilized habitat suitability modelling to assess the ecological preferences of *Cedrus deodara* (Roxb. ex D.Don) G.Don, a keystone Himalayan conifer and Pakistan's national tree. Species occurrence data were gathered from field surveys and online sources. A total of 39 climatic, topographic and hydrological variables were analyzed, of which 16 were selected for the environmental species distribution model (E-SDM), while 6 climatic variables were used for the climate-only species distribution model (C-SDM). The E-SDM produced more reliable habitat predictions after incorporating topographic and hydrological variables. Although the C-SDM showed slightly higher AUC values (0.987 training; 0.925 testing), the E-SDM performed better in sensitivity (0.981), specificity (0.915) and TSS (0.904). Climatic variables mainly influenced the C-SDM, whereas moisture availability and terrain conditions strongly influenced the E-SDM. These results indicate the importance of local environmental conditions in determining the distribution of *C. deodara*. The E-SDM also identified a larger suitable habitat area (21473 km^2) compared to the C-SDM (17559 km^2), including additional potential conservation regions. Future projections showed relatively minor habitat shifts under SSP370, whereas SSP585 projected an initial expansion of suitable habitat by 2041-2070 (24378 km^2), followed by a decline towards 2071-2100 (20756 km^2) under intensified warming conditions. The study indicated climate-induced habitat shifts, emphasizing the need to prioritize conservation and restoration efforts in climatically stable and environmentally suitable regions identified in Khyber Pakhtunkhwa, Gilgit-Baltistan and Azad Jammu and Kashmir. Future suitable habitats projected under SSP scenarios may support assisted regeneration, afforestation and long-term monitoring programmes to improve the persistence of *C. deodara* under changing climate conditions.

Key words: Deodar; Climate change; Conservation; Habitat suitability; Species distribution modelling.

Introduction

Cedrus deodara (Roxb. ex D.Don) G.Don, commonly known as Deodar or Himalayan Cedar, belongs to the family Pinaceae. *C. deodara* is recognized for its high-quality coniferous timber. The species occurs in dry temperate to subalpine Himalayan regions at elevations of approximately 1200-3000 m, extending across northern Pakistan, western Nepal, eastern Afghanistan and south-western Tibet (Naikoo *et al.,* 2017; Bisht *et al.,* 2021). It is an evergreen conifer with horizontal branches, glaucous-green needle-like leaves and barrel-shaped female cones (Chaudhary *et al.,* 2011; Khan *et al.,* 2013). *C. deodara* reaches 45-60 m in height and 0.8-1.1 m in diameter, with a mean annual growth rate of 0.23 ± 0.073 cm, wood density of 466 kg m^{-3} and mean annual increment of 1.19 m^3 ha^{-1} (Nasir & Shah, 2014; Ahmad *et al.,* 2018; Wani *et al.,* 2014). The species prefers deep, humid and well-drained soils but is sensitive to severe frost and cold winds during early growth stages (Pandey *et al.,* 2023).

C. deodara has considerable ecological, cultural and economic importance. It is regarded as sacred in Hindu traditions and associated with Lord Shiva (Pathak *et al.,* 2023). The species possesses medicinal properties, with its oil and bark extracts used for treating fever, dysentery, diarrhoea and inflammation (Gacche & Dhole, 2006). Its oil is also utilized in soaps, perfumes and insect-resistant products due to anti-moth and termite-resistant properties (Nirala *et al.,* 2022; Monks *et al.,* 1991). It is also used in Chinese herbal medicine and ornamental landscaping (Zhang *et al.,* 2009; Negi, 2022). *C. deodara* is extensively used in furniture, construction and carpentry (Sher *et al.,* 2023). The species also contributes significantly to biomass carbon storage and climate change mitigation, with reported carbon dioxide mitigation potential (Sheikh *et al.,* 2021; Wani *et al.,* 2014; Ahmad *et al.,* 2015).

However, *C. deodara* forests in the Himalayan region are particularly vulnerable to human influence and climate change due to their limited range and evolutionary persistence in these sensitive habitats (Trew & Maclean, 2021; Yadava *et al.,* 2021). Global warming has triggered a 38% decline in the growth of *C. deodara*, driven by rising temperatures, increased drought stress and shifting species dynamics, making it a species with the highest Conservation Priority Index (Rana *et al.,* 2020). Moreover, the upward migration of drought and fire-tolerant species (e.g., *Pinus roxburghii*) intensifies threats to *C. deodara* at lower elevations (Bhattacharyya *et al.,* 2023) and it is

Received: 18-03-2026 | Revised: 12-05-2026 | Accepted: 20-05-2026 | Online: 05-11-2026

expected to migrate towards higher elevations and has the potential to compete with subalpine and timberline species (Durrani *et al.,* 2024).

Species distribution modelling (SDM) approaches are based on statistical or machine learning techniques used to predict the potential distribution of species by analyzing relationships between species occurrence records and environmental variables (Merow *et al.,* 2016; Warren *et al.,* 2020; Muscatello *et al.,* 2021). These models integrate known presence locations with climatic, topographic and ecological factors to identify areas with suitable environmental conditions for species survival, growth and persistence. SDM techniques can explain species distribution patterns and forecast potential shifts under different environmental and climate conditions (Gonzalez-Aragon *et al.,* 2024).

By evaluating spatial and temporal environmental constraints through different methods and algorithms (Pearson *et al.,* 2007), SDMs provide spatially explicit predictions that are widely used to assess habitat suitability, understand species-environment relationships and examine responses to climate change. SDMs can also help identify marginal populations, suitable sites for species reintroduction and priority areas for conservation. Their ability to predict habitat suitability under varying environmental conditions has made them useful tools for biodiversity conservation, resource management and ecological planning (Thakur *et al.,* 2021).

Populations of *C. deodara* have declined in the Himalayan region due to rising temperatures, forest disturbance and increasing human pressure (Kumar & Pandey, 2024). In Pakistan, deforestation, habitat degradation and environmental change further threaten species by limiting its natural regeneration (Zeb *et al.,* 2019; Hayat *et al.,* 2021). Species distribution models are increasingly used to examine how environmental conditions influence habitat suitability and future distribution patterns, providing useful information for forest conservation and management planning (Huang *et al.,* 2024). In the present study, SDM techniques were applied to evaluate the habitat suitability of *C. deodara*, an ecologically and economically important Himalayan conifer (Pandey *et al.,* 2023).

This study assumed that adding topographic and hydrological variables to climatic factors may improve SDMs for *C. deodara* in northern Pakistan. These variables are often overlooked and crucial terrain influences on species distribution in mountainous areas are not well understood. By integrating high-resolution environmental data and future climate projections, this study addresses these gaps to produce more accurate predictions of habitat suitability under changing climate conditions. The objectives of this study were to (i) identify the topo-climatic factors influencing the distribution of *C. deodara*, (ii) compare the performance of climate-only and environmental species distribution models, and (iii) predict current and future habitat suitability under different climate change scenarios in northern Pakistan. The findings support conservation and reforestation planning under rising climate and human pressures. This research aligns global sustainability efforts, supporting Sustainable Development Goal (SDG) 15 (Life on Land) by promoting ecosystem sustainability and biodiversity conservation and SDG 13 (Climate Action) by advocating sustainable forest management practices to mitigate climate change impacts.

Materials and Methods

Study area: The study covered northern Pakistan between 69.5°E-78°E and 32.5°N-37.5°N, with a total area of 279649 km^2 (Fig. 1). The region includes rugged mountain systems, foothill landscapes and low-elevation plains. Considerable variation in elevation, temperature and moisture conditions occurs across the area, particularly within the western Himalayan belt (Ali *et al.,* 2021). Forest cover in Pakistan remains limited, occupying nearly 3.725 million hectares or about 4.7% of the country's total area (Ali *et al.,* 2023). The study region is primarily characterized by coniferous forests, including Himalayan moist temperate, dry temperate and sub-tropical pine forests. Other prominent forest types include subtropical broad-leaved evergreen forests, mixed forests, linear plantations and trees on private lands (Rasheed *et al.,* 2017). The study area was selected because it represents natural distribution range of *C. deodara* in Pakistan. The region contains diverse climatic, topographic and hydrological conditions suitable for evaluating habitat variability and future climate-driven distribution shifts.

Climate: Pakistan, especially the northern region is significantly susceptible to the negative impacts of climate change, particularly due to rising temperatures, variability of monsoons, melting Himalayan glaciers and a rise in both the frequency and intensity of extreme weather events and natural disasters (Malik *et al.,* 2012; Fahad & Wang, 2020). The eastern part of the southern region predominantly receives rainfall during the monsoon season (June to September), whereas the northern and western areas depend on winter precipitation (December to March). The summer monsoon accounts for 60% of the total annual rainfall. Most of the region experiences arid to semi-arid conditions, with annual precipitation generally below 250 mm. However, in the northern study area, rainfall varies between 760 and 2000 mm. This northern region is characterized by towering mountains and extensive glaciers, where winter temperatures can drop to -50°C (Chaudhry, 2017; Latif *et al.,* 2017).

Species occurrence data collection: Species occurrence points were recorded through systematic field surveys conducted between March 2023 and December 2024. Surveys were carried out along accessible forested routes within the known and potential range of *C. deodara*. Geographic coordinates of each occurrence were recorded using a handheld GPS device. The secondary data for presence points were noted using online data sources, i.e., the Global Biodiversity Information Facility (Anon., 2025). To ensure consistency with the climatic and topographic data used in this study, coordinates were verified duplicate records were removed. Occurrence points were spatially filtered to reduce sampling bias and ensure consistency with the 1 km^2 environmental raster resolution. After filtering, 160 unique occurrence points, each representing a distinct location within the environmental raster layer, were selected to model the habitat suitability of *C. deodara* in Pakistan (Fig. 2).

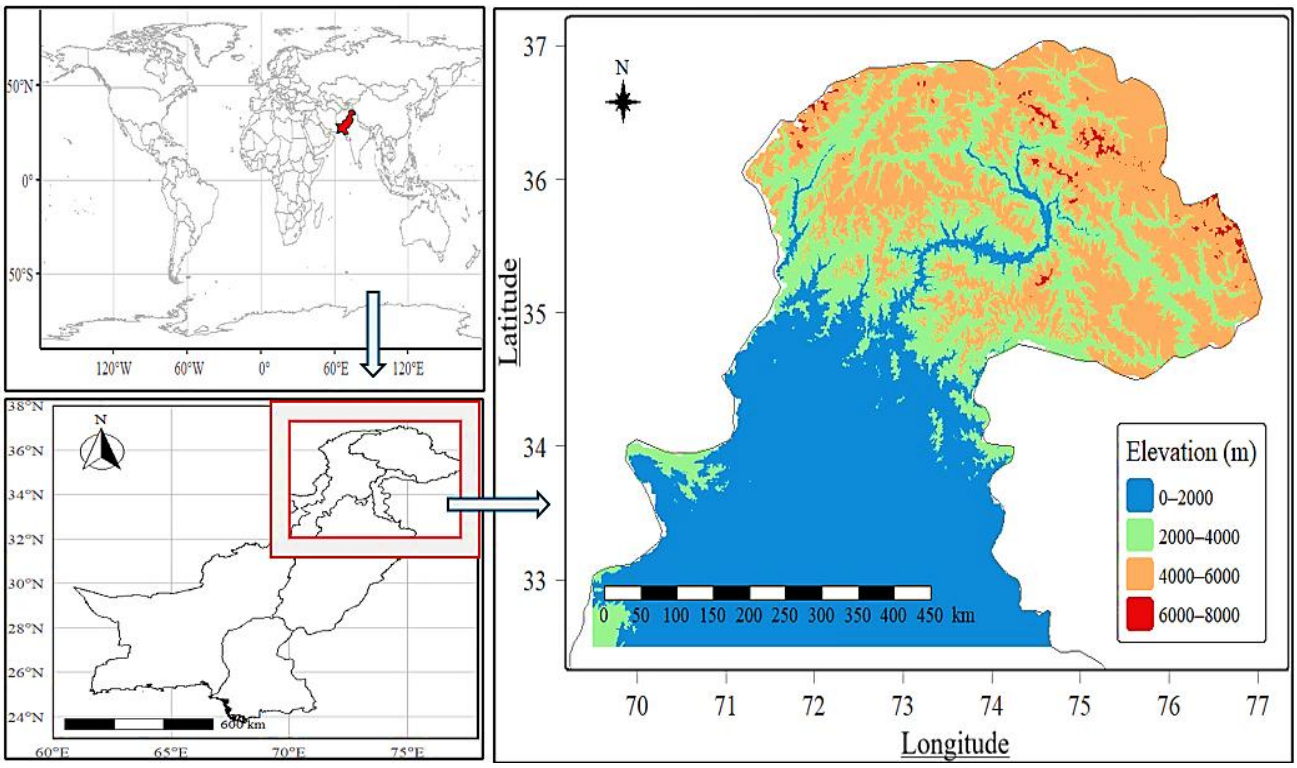


Fig. 1. Map depicting the study area in northern Pakistan, showing the regional extent within Asia and Pakistan, along with elevation distribution and elevation classes across the study region.

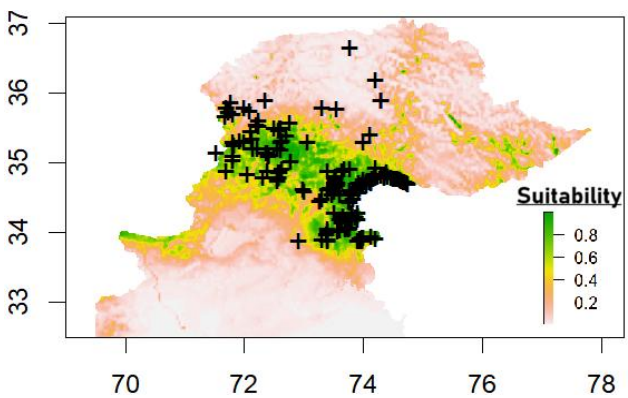


Fig. 2. Map of the study area showing recorded occurrence points of *C. deodara* and probability of occurrence derived using bioclimatic and topographic data.

Climatic and topographic data: Bioclimatic data from the Climatologies at High Resolution for the Earth's Land Surface Areas (CHELSA) version 2.1 was utilized to evaluate the habitat suitability of *C. deodara*. This dataset includes 19 ecologically relevant climatic variables derived from spatially interpolated historical climate data spanning 1981-2010 (Karger *et al.,* 2021). CHELSA offers high-resolution estimates of temperature and precipitation at a 30 arc-second grid scale, using statistical downscaling for temperature and orographic predictors with bias correction for precipitation (Karger *et al.,* 2017; Beck *et al.,* 2020).

Future climate projections were obtained from the GFDL-ESM available through CHELSA datasets. The model simulates interactions among atmospheric, oceanic, terrestrial and sea ice systems together with biogeochemical processes. Owing to its ability to represent large-scale climate variability, GFDL-ESM has been widely applied in CMIP-based climate assessments (Dunne *et al.,* 2020; Zhao *et al.,* 2018).

To assess future habitat shifts of *C. deodara*, two Shared Socioeconomic Pathways (SSPs), SSP370 and SSP585, were selected for the periods 2041–2070 and 2071–2100. These scenarios represent moderate and high-emission trajectories and were used to examine potential long-term changes in habitat suitability relevant to conservation planning. SSP370 depicts a medium-to-high emissions trajectory characterized by regional rivalry, limited international cooperation and weak climate policies. In contrast, SSP585 represents a fossil-fueled development pathway resulting in very high greenhouse gas emissions and strong radiative forcing by the end of the century (Higgins *et al.,* 2023).

The elevation dataset, with a spatial resolution of 30 arc seconds, was obtained from the WorldClim database (Fick & Hijmans, 2017). The terra package (Hijmans, 2025) in R (v4.4.2) software (R Core Team, 2025) was used to derive topographical and hydrological features, including slope, aspect, hillshade, drainage and flow-related variables. A total of 20 topographic and hydrological variables were extracted to be used in the SDM of *C. deodara*.

Data processing: SDM was carried out using two approaches. First, a Climate-Only Species Distribution Model (C-SDM) was developed using bioclimatic variables from the baseline period (1981-2010) and future climate projections (2041-2070 and 2071-2100) under SSP370 and SSP585 scenarios. This model was primarily used to evaluate the influence of climate variables on species distribution and to assess potential habitat shifts under future climate change conditions. Secondly, an Environmental Species Distribution Model (E-SDM) was developed by integrating climatic, topographic and hydrological variables. The inclusion of environmental variables aimed to account

for terrain-related factors that influence species distribution in mountainous ecosystems. Using both approaches enabled a comparison between climate-driven and environment-integrated predictions. Moreover, it assessed the added contribution of topographic and hydrological factors in improving SDM and prediction accuracy for *C. deodara*.

Environmental predictors were loaded into R as a multi-layer raster stack. Environmental values for each presence location were extracted and missing values were removed to maintain data integrity. A total of 1000 pseudo-absence points were sampled within the study extent. The number of pseudo-absences was selected based on model sensitivity analyses to maintain a balanced presence-to-absence ratio. Environmental data for *C. deodara* occurrence points were extracted, missing values were removed and a binary response variable was assigned (1 for presence, 0 for pseudo-absence).

Environmental variables with minor variance were removed to reduce multicollinearity and a correlation matrix was computed (Wei & Simko, 2024). Environmental variables with a Pearson correlation coefficient exceeding 0.7 were then excluded to minimize multicollinearity and retain independent predictors, following established recommendations in species distribution modelling (Dormann *et al.,* 2013). The C-SDM maintained 6 of 19 bioclimatic variables (Bio2, Bio7, Bio8, Bio9, Bio13 and Bio15) while E-SDM for *C. deodara* incorporated 16 of the 39 environmental variables (Table 1). SDM was performed using the dismo package (Hijmans *et al.,* 2024). All analyses were performed using R (R Core Team, 2025) software (version 4.4.2).

Model training, validation and performance evaluation: The final dataset included selected environmental predictors, geographic coordinates and presence-absence labels. A 10-fold cross-validation approach was used in SDM. The dataset was partitioned into 10 folds, preserving the proportion of presence and pseudo-absence points. Each fold produced a test set once, while the remaining nine were used for training. After testing, a fixed random seed (set.seed(42)) was applied to ensure reproducibility of the sampling process. In each iteration, the dataset was split into training and testing subsets and a binomial logistic regression model was applied using the glm function (Hijmans *et al.,* 2024). The fitted model generated probability scores for both training and test datasets, representing the likelihood of *C. deodara* presence at each location. Habitat suitability of *C. deodara* was predicted in raster format using environmental variables, where values ranged from 0 (unsuitable habitat) to 1 (highly suitable habitat).

Table 1. Details of environmental variables used for environmental species distribution modelling of *C. deodara* and correlation-based variable selection.

No.	Variable name	Description	Category	Decision
1.	Aspect	The compass direction (0-360°) that a slope faces.	Topographic	Retained
2.	Aspect difference	Variation in aspect between adjacent cells.	Topographic	Removed
3.	Bio1	Annual mean temperature	Climatic	Removed
4.	Bio2	Mean diurnal range (mean of monthly max temp - min temp)	Climatic	Retained
5.	Bio3	Isothermality (Bio2 / Bio7) (* 100)	Climatic	Removed
6.	Bio4	Temperature seasonality (standard deviation * 100)	Climatic	Removed
7.	Bio5	Max temperature of warmest month	Climatic	Removed
8.	Bio6	Min temperature of coldest month	Climatic	Removed
9.	Bio7	Temperature annual range (Bio5 - Bio6)	Climatic	Retained
10.	Bio8	Mean temperature of wettest quarter	Climatic	Retained
11.	Bio9	Mean temperature of driest quarter	Climatic	Retained
12.	Bio10	Mean temperature of warmest quarter	Climatic	Removed
13.	Bio11	Mean temperature of coldest quarter	Climatic	Removed
14.	Bio12	Annual precipitation	Climatic	Removed
15.	Bio13	Precipitation of wettest month	Climatic	Removed
16.	Bio14	Precipitation of driest month	Climatic	Removed
17.	Bio15	Precipitation seasonality (coefficient of variation)	Climatic	Retained
18.	Bio16	Precipitation of wettest quarter	Climatic	Removed
19.	Bio17	Precipitation of driest quarter	Climatic	Removed
20.	Bio18	Precipitation of warmest quarter	Climatic	Retained
21.	Bio19	Precipitation of coldest quarter	Climatic	Removed
22.	Compound topographic index	The potential for water accumulation in a landscape.	Hydrological	Removed
23.	Cumulative aspect	Sum of aspect values over a defined area	Topographic	Removed
24.	Cumulative slope	Sum of slope values over a defined area	Topographic	Removed
25.	Drainage density	Total length of streams per unit area, indicating drainage efficiency	Hydrological	Retained
26.	Elevation	Height above sea level, measured in meters	Topographic	Removed
27.	Flow accumulation	Number of upstream cells contributing to flow at a given location	Hydrological	Retained
28.	Flow direction	Direction of water movement based on elevation gradients	Hydrological	Retained
29.	Hillshade	Simulated illumination of terrain based on light source angle	Topographic	Retained
30.	Plan curvature	Curvature of the terrain surface in the horizontal plane, influencing water flow	Topographic	Retained
31.	Profile curvature	Curvature in the vertical plane, affecting erosion and deposition processes	Topographic	Retained
32.	Relative elevation	Elevation relative to surrounding terrain features	Topographic	Removed
33.	Roughness	Variation in elevation values, indicating surface irregularity	Topographic	Removed
34.	Slope	Steepness of the terrain, measured in degrees or percent rise	Topographic	Removed
35.	Slope gradient index	Measure of slope variability across a region	Topographic	Removed
36.	Stream power	Energy of flowing water, influencing erosion potential.	Hydrological	Retained
37.	Terrain ruggedness index	Quantifies terrain complexity based on elevation differences	Topographic	Removed
38.	Topographic position index	Differentiates valleys, mid-slopes and ridges based on elevation differences	Topographic	Retained
39.	Topographic wetness index	Indicates soil moisture potential based on slope and flow accumulation	Hydrological	Retained

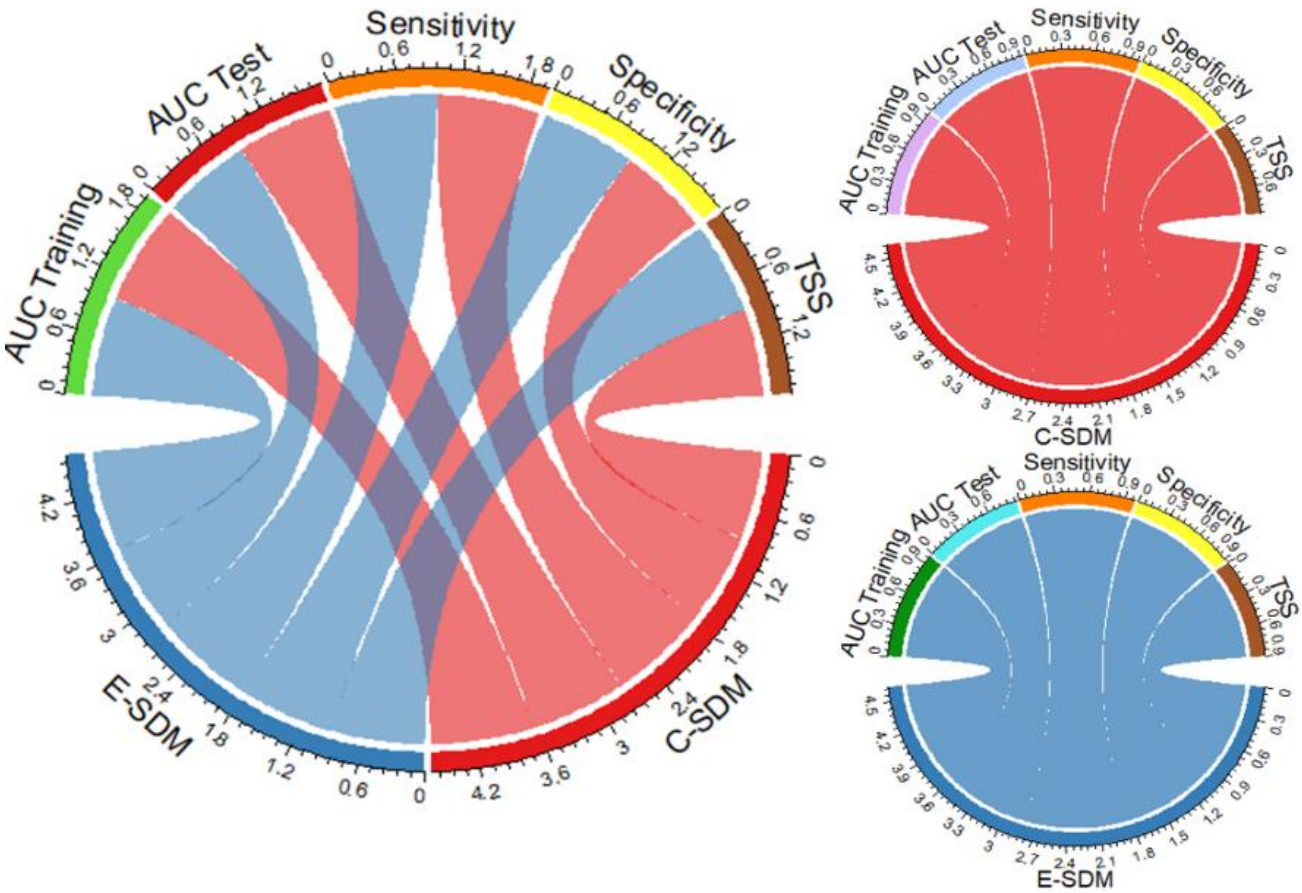


Fig. 3. Performance evaluation metrics for C-SDM and E-SDM in predicting the distribution of *C. deodara* in the study area.

The predictive performance of C-SDM and E-SDM was evaluated using multiple accuracy measures. Area under the curve (AUC) was used to assess the ability of the models to distinguish presence from absence locations. Sensitivity and specificity were also calculated to evaluate classification accuracy (Shabani, 2018; Muscatello *et al.,* 2021). Sensitivity represented correctly predicted presence records, whereas specificity indicated correctly classified pseudo-absence points. Predicted probabilities were converted to binary classifications using a 0.75 threshold to reflect a high-confidence prediction of species presence. Values above 0.75 were classified as presence (1) and below as absence (0). True Skill Statistic (TSS), a comparatively more realistic and practical method (Shabani, 2018) was also computed. After cross-validation, mean values for AUC, sensitivity, specificity and TSS were calculated across all folds for overall model evaluation. Model performance metrics were plotted using circlize package in R (R Core Team, 2025; Gu *et al.,* 2014).

Results

Model performance evaluation: Model evaluation showed that both the C-SDM and E-SDM effectively predicted the distribution of *C. deodara* in northern Pakistan. The C-SDM achieved a mean AUC of 0.987 (training) and 0.925 (testing), with slight overprediction. It showed high sensitivity (0.97) and specificity (0.90) and a TSS of 0.86, indicating strong overall performance (Fig. 3). The E-SDM, which incorporated topographic and hydrological variables, produced a mean AUC of 0.977 and a testing AUC of 0.86. Although the test AUC was slightly lower, it showed higher sensitivity (0.981), specificity (0.915) and a greater TSS (0.904) than the C-SDM (Fig. 3). These results suggest that adding topographic and hydrological predictors improved the model's ability to identify suitable habitats.

Spatial distribution of *C. deodara* habitat suitability: SDMs revealed that in Azad Jammu and Kashmir (AJK), suitable habitats of *C. deodara* are present in Muzaffarabad, Neelum Valley, Poonch and Bagh districts. The temperate forests of Neelum Valley are extraordinarily suitable for *C. deodara*. In the Gilgit-Baltistan (GB) region, habitat suitability was recorded in the Gilgit, Skardu, Hunza, Diamer, Astore and Ghanche districts. Among these, Diamer, especially near Chilas, demonstrates strong suitability of habitat. Hunza and Astore also support suitable habitat conditions, where stable populations occur in sheltered valleys and mountain slopes with favourable moisture and temperature conditions (Fig. 4).

Khyber Pakhtunkhwa province (KPK) represented a major stronghold for *C. deodara*, particularly in Swat, Shangla, Upper Dir, Lower Dir, Kohistan, Mansehra, Abbottabad and Torghar districts. Swat district (specifically Malam Jabba and Kalam regions) already exhibit higher habitat suitability of *C. deodara*. Similarly, the Kaghan Valley in Mansehra district is also an important habitat. The forests of Kohistan and Dir may further support *C. deodara* populations, although their distribution may be more fragmented due to topographical variations and human activities.

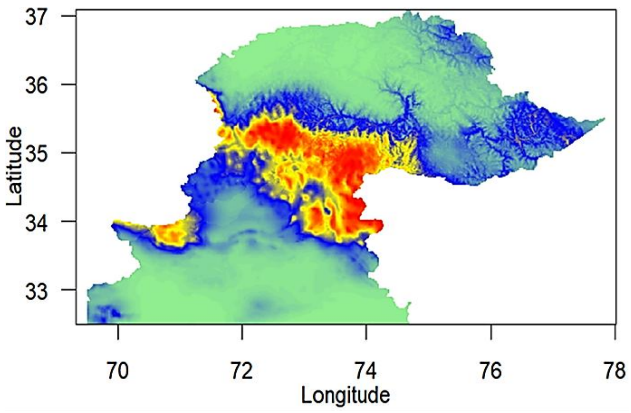


Fig. 4. Current habitat suitability predictions for *C. deodara* in northern Pakistan.

In Punjab province, *C. deodara* habitat suitability is primarily found in Murree hills, where the species grows in the surrounding forest reserves (Fig. 4). The total study area assessed for habitat suitability spanned 279649 km^2. Based on C-SDM, a total of 17559 km^2 (6.28%) was identified as suitable for *C. deodara*, indicating significant habitat limitations under climatic constraints alone. In contrast, E-SDM estimated a larger suitable area (7.68%) of 21473 km^2 (Table 2).

Table 2. Summary of habitat suitability projections for *C. deodara* under current and future climate scenarios.

Climate model	Period	Suitable area (Km^2)	Unsuitable area (Km^2)	Suitable area (%)
C-SDM	Current	17559	262090	6.28
E-SDM	Current	21473	258176	7.68
SSP370	2041-2070	17816	261833	6.37
SSP370	2071-2100	18946	260703	6.77
SSP585	2041-2070	24378	255271	8.71
SSP585	2071-2100	20756	258893	7.42

Habitat suitability projection under future climate scenarios: Future climate scenarios projected both gains and losses in suitable habitat for *C. deodara*, with expansions primarily occurring in higher elevation zones and northeastern regions of the study area, particularly within the Himalayas and upper Hindukush regions. The extent of fluctuation varies across different periods (Fig. 5). Under the SSP370 scenario, habitat suitability projections indicated variations over time. By 2070, the total suitable habitat is projected to be 17816 km^2, while 261833 km^2 is classified as unsuitable. By 2100, the suitable habitat is expected to increase to 18946 km^2, reducing the unsuitable area to 260703 km^2. Projections showed a marginal expansion of *C. deodara* habitat under the SSP370 scenario, with a gradual increase in suitability over time (Fig. 5).

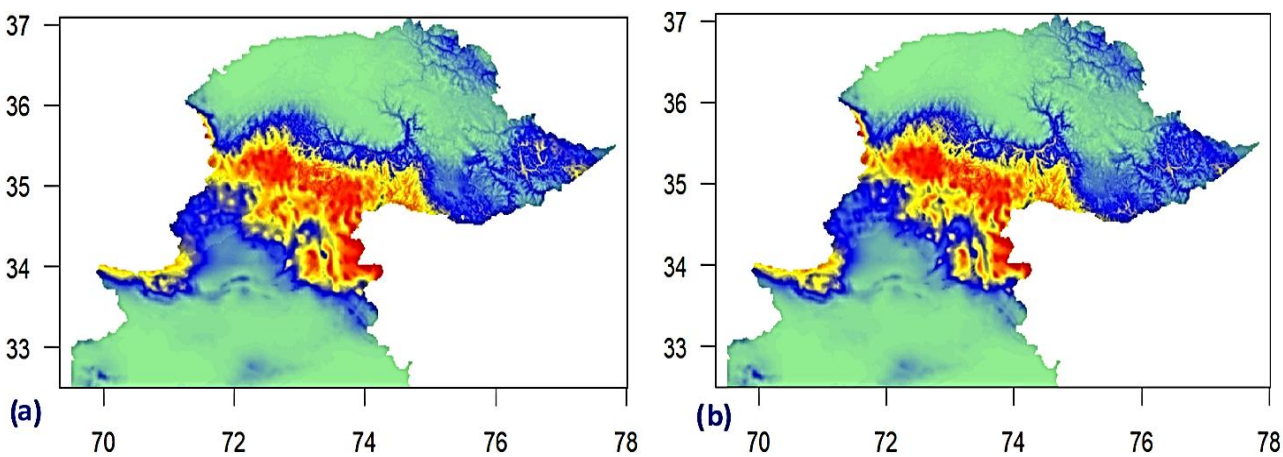


Fig. 5. Temporal and spatial variations in *C. deodara* habitat distribution within the study area as predicted by E-SDM under SSP370 for the period (a) 2041-2070 and (b) 2071-2100.

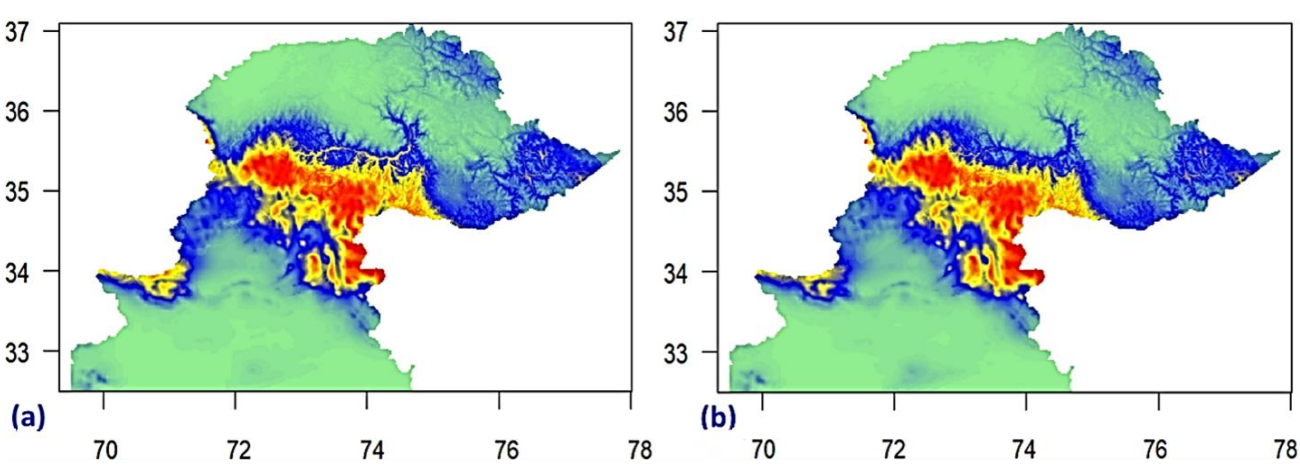


Fig. 6. Temporal and spatial variations in *C. deodara* habitat distribution within the study area as predicted by E-SDM under SSP585 for the period (a) 2041-2070 and (b) 2071-2100.

Table 3. Contribution of environmental variables in C-SDM and E-SDM for *C. deodara* habitat suitability.

No.	Variable	C-SDM contribution (%)	E-SDM contribution (%)
1.	Aspect	-	0.21
2.	Bio13	2.51	Removed/Correlated
3.	Bio15	28.27	1.83
4.	Bio18	Removed/Correlated	0.1
5.	Bio2	18.34	0.39
6.	Bio7	38.48	0.44
7.	Bio8	3.51	0.47
8.	Bio9	8.87	1.43
9.	Drainage density	-	0
10.	Flow accumulation	-	0.55
11.	Flow direction	-	2.36
12.	Hillshade	-	38.56
13.	Plan curvature	-	0.55
14.	Profile curvature	-	0.86
15.	Stream power	-	1.44
16.	Topographic position index	-	0.33
17.	Topographic wetness index	-	50.48

Under the SSP585 scenario, habitat suitability projections exhibited more evident fluctuations over time. By 2070, the total suitable habitat is expected to increase significantly to 24378 km^2, reducing the unsuitable area to 255271 km^2. However, by 2100, the suitable habitat is projected to decline to 20756 km^2, with 258893 km^2 classified as unsuitable. This trend suggests a substantial expansion of *C. deodara* habitat by mid-century, followed by a contraction towards the end of the century (Fig. 6).

Analysis of variable contribution: Habitat suitability patterns of *C. deodara* differed between C-SDM and E-SDM due to the influence of climatic, topographic and hydrological variables. The C-SDM predicted suitability mainly from climatic conditions, whereas the E-SDM produced more ecologically detailed predictions after incorporating terrain and moisture-related variables. In the C-SDM, Bio7 (38.48%) and Bio15 (28.27%) showed the highest contributions, indicating the importance of annual temperature range and precipitation seasonality. Bio2 (18.34%) and Bio9 (8.87%) also contributed substantially, reflecting the influence of seasonal temperature and moisture conditions on species distribution (Table 3).

In contrast, the inclusion of topographic and hydrological variables in the E-SDM shifted the dominant factors controlling habitat suitability. The Topographic Wetness Index (50.48%) emerged as the most influential factor, while Hillshade (38.56%) underscored the role of terrain shading and solar radiation. Flow Direction (2.36%) and Stream Power (1.44%) also played minor roles in shaping *C. deodara* habitat in the study area. Climatic factors in E-SDM played a comparatively smaller role, with Bio15 (1.83%), Bio9 (1.43%) and Bio8 (0.47%) exhibiting reduced influence. Bio7, which was the primary driver in C-SDM, contributed only 0.44% in E-SDM, by underlining the shift toward topography-driven habitat suitability (Table 3).

Discussion

Understanding the ecological determinants of *C. deodara* distribution is important for its conservation and prediction of the impacts of environmental changes (Bhattacharyya *et al.,* 2023). This study employed the SDM technique to evaluate the habitat suitability of *C. deodara* in Pakistan under current and future climate scenarios. The study analyzed key environmental variables and projected habitat shifts based on both present and future climate scenarios. The produced habitat suitability map provides information about the potential distribution of this ecologically vital tree species. The model identified areas with different suitability levels for *C. deodara*, predominantly located in northern mountainous regions of Pakistan, covering the Himalayas, Karakoram and Hindu Kush ranges. These regions provide favourable temperature and moisture conditions for the growth of *C. deodara.*

The findings of this study align well with previous studies on the natural distribution of *C. deodara* in Pakistan, particularly its prevalence in the western Himalayas and mountainous regions (Ahmed *et al.,* 2010; Ahmed *et al.,* 2011; Ali *et al.,* 2016; Sajad *et al.,* 2021; Zaman *et al.,* 2018). This study identified the ecological factors shaping the distribution of *C. deodara* in Pakistan under changing climate scenarios and illustrated areas for focused conservation efforts. High-suitability regions with known ranges could be future habitats for reforestation, afforestation and species introduction programs, especially in response to climate change (Chen *et al.,* 2022). Moreover, the current distribution modelling of *C. deodara* also serves as a proxy for the habitat patterns of ecologically similar temperate coniferous species, including *Pinus wallichiana*, *Picea smithiana* and *Abies pindrow*. Additionally, it reflects the broader distribution of associated flora comprising key genera such as *Quercus*, *Acer*, *Juniperus*, *Cotoneaster* and *Viburnum* (Rahman *et al.,* 2023).

Under current climatic conditions, *C. deodara* is mostly found in western and northern mountainous regions of Pakistan, especially within KPK, GB and AJK. This spatial pattern shows the species' dependence on temperate climates and specific temperature and precipitation regimes essential for survival. Past studies have revealed a strong correlation between the ecological niche of *C. deodara* and the prevailing climatic and topographic gradients in these regions (Ahmed *et al.,* 2010; Chaudhary *et al.,* 2011; Khan *et al.,* 2013; Nasir & Shah, 2014; Wani *et al.,* 2014; Ahmad *et al.,* 2018; Shah *et al.,* 2018; Zaman *et al.,* 2018; Sheikh *et al.,* 2021; Nirala *et al.,* 2022; Ali *et al.,* 2023; Bhattacharyya *et al.,* 2023; Pandey *et al.,* 2023).

Under the SSP370 scenario, suitable habitat of *C. deodara* showed only minor changes over time. This suggests that moderate warming may still support the persistence of the species in higher elevation areas where environmental conditions remain suitable. However, the limited expansion indicates sensitivity of the species to shifts in seasonal temperature and precipitation patterns. In northern Pakistan, *C. deodara* is associated with cool, moist montane environments. Under SSP585, suitable habitat is projected to expand during 2041-2070, particularly at higher elevations of the Himalayan and Hindu Kush regions. This pattern suggests that rising temperatures may drive the upslope expansion of *C. deodara* into higher-elevation areas that are currently limited by low temperatures. However, by 2071-2100, suitable habitat is projected to decline, suggesting that continued warming and increasing moisture stress may reduce habitat suitability at lower elevations and constrain further upward expansion.

As *C. deodara* depends on stable moisture conditions, prolonged warming may also affect regeneration and long-term stand stability. The projected decline under late-century SSP585 therefore indicates that initial habitat gains under warm conditions may not remain stable under prolonged climate stress. While moderate warming may expand habitat suitability in high-altitude areas, more extreme climate scenarios may lead to more habitat modifications and range shifts (Kumar & Khanduri, 2024; Balu *et al.,* 2023; Bouahmed *et al.,* 2019).

Habitat suitability of *C. deodara* is influenced by specific niche preferences and association among environmental variables (Khan *et al.,* 2013; Nirala *et al.,* 2022; Bhattacharyya *et al.,* 2023) as revealed by SDM. C-SDM indicated that seasonal temperature range, daily variability and precipitation patterns define the species' niche. In contrast, the E-SDM shifted the pattern and the Topographic Wetness Index, along with Hillshade, emerged as the principal predictors, emphasizing the roles of soil moisture, water availability and terrain shading.

The E-SDM demonstrated better ecological discrimination capacity. This indicates that the E-SDM was more effective in correctly identifying both suitable and unsuitable habitats of *C. deodara* across the heterogeneous mountainous landscapes of northern Pakistan. The relatively higher AUC in C-SDM mainly reflects the strong predictive influence of broad-scale climatic variables, particularly temperature range and precipitation seasonality. However, climate-only models may oversimplify habitat suitability in mountainous ecosystems where local terrain conditions strongly regulate microclimate, soil moisture availability, solar radiation exposure and water flow patterns. The inclusion of topographic and hydrological variables in E-SDM improved the modelling outputs by capturing fine-scale environmental heterogeneity that directly influences species establishment and persistence.

This interpretation is further supported by the variable contribution analysis, where Topographic Wetness Index and Hillshade emerged as dominant predictors in E-SDM, while climatic variables contributed comparatively less. These findings indicate that moisture retention, terrain shading and hydrological processes play an important role in shaping the habitat suitability of *C. deodara* in the study area. Therefore, E-SDM provided a more balanced and ecologically meaningful prediction of species distribution compared to the C-SDM. The inclusion of multiple environmental variables improved ecological niche prediction in mountainous landscapes (Ali *et al.,* 2023).

Distribution of *C. deodara* is closely linked with elevation, slope conditions and local climate. Growth and regeneration decline under severe thermal conditions, particularly at very low or high temperatures. Seasonal snow contributes to moisture retention, whereas irregular precipitation patterns may alter growth cycles and increase susceptibility to pests. Moist north-facing slopes and moderate terrain gradients generally favour *C. deodara* establishment, whereas steep slopes may limit seedling survival due to reduced soil stability and moisture retention (Kim *et al.,* 2018; Sheikh *et al.,* 2021; Moulatlet *et al.,* 2022; Pandey *et al.,* 2023). In mountainous environments, terrain and moisture-related conditions can strongly influence habitat suitability and may locally override broader climatic controls (Kim *et al.,* 2018; Moulatlet *et al.,* 2022).

Several factors contributed in the decline of *C. deodara* in the study region. Forest clearing, illegal timber extraction and pressure from non-timber resource use continue to reduce natural stands. Changes in precipitation patterns and increasing climatic variability may further affect regeneration and long-term survival. In some areas, habitat fragmentation, invasive species (*Lantana camara* and *Parthenium hysterophorus,* etc.) pathogen susceptibility and land degradation have also affected population stability. Poor seedling establishment under intensive grazing pressure remains an additional concern for natural regeneration (Zeb *et al.,* 2019; Hayat *et al.,* 2021; Ansari *et al.,* 2022; Bhattacharyya *et al.,* 2023).

Long-term protection of *C. deodara* forests will require management approaches adapted to future environmental conditions. The present study identified areas likely to remain suitable under future climate scenarios, which may support conservation, assisted regeneration and reforestation activities. Differences in habitat suitability among SSP scenarios also indicate that management priorities may vary spatially across northern Pakistan (Durrani *et al.,* 2024). In contrast, areas projected to lose suitability may require restoration measures, stricter control of anthropogenic activities, protection of local moisture regimes, and improved connectivity among fragmented forest patches. Conservation efforts should also include the least suitable areas, address underlying limitations and facilitate species migration. SSP-based

projections enable proactive strategies to sustain *C. deodara* populations amid changing climatic conditions (Abrha *et al.,* 2024).

Several regions of Pakistan may support future expansion of *C. deodara* under suitable environmental conditions (Khan *et al.,* 2013; Xiao *et al.,* 2022). In northern KPK and GB, areas such as Shangla, Upper Dir and Chitral contain favourable elevational and climatic conditions for the species (Abbas *et al.,* 2023). The modelling results also identified suitable habitats in parts of Punjab, including Murree, Galyiat and Margalla hills. In AJK, elevated regions of Poonch and Muzaffarabad, particularly Neelum Valley and Upper Jhelum Valley, also showed potential for afforestation and regeneration activities. Successful introduction requires assessing flora, fauna and soil properties like drainage and nutrient availability to minimize ecosystem disruption (Ahmad *et al.,* 2018; Gilani *et al.,* 2020). Climate projections must also be considered to prioritize areas maintaining long-term suitability (Bouahmed *et al.,* 2019).

Field data and ground truthing confirm that habitat fragmentation is primarily driven by deforestation and development (Debebe *et al.,* 2023). The current research highlights key hotspots for targeted conservation strategies to protect ecological communities linked to *C. deodara* (Ma *et al.,* 2023). Conservation efforts should prioritize reconnecting fragmented areas, address degradation, implement assisted regeneration in low-density stands and promote natural vegetation recovery (Kassa *et al.,* 2023). Protecting erosion in moist (north-facing) slopes, safeguarding seedlings and regulating grazing are necessary conservation measures. Mitigation strategies include climate-resilient planning, sustainable forestry and community involvement through education. Effective habitat suitability modelling for conservation necessitates addressing methodological challenges, fostering interdisciplinary collaboration, validating predictions with independent data, ensuring accessibility of results and enhancing capacity building (Merow *et al.,* 2016; Zingraff-Hamed *et al.,* 2018; Zellmer *et al.,* 2019; Bishop *et al.,* 2021).

SDMs are mostly valuable for predicting species distributions in data-limited scenarios. However, overfitting can introduce complexity and overemphasize certain environmental predictors (Warren *et al.,* 2020). To mitigate this, cross-validation was employed, which partitioned data into training and testing sets. Cross-validation enhances model generalizability, while field verification ensures reliability by identifying biases (Merow *et al.,* 2016). Model performance was assessed through AUC, sensitivity, specificity and TSS, confirming optimal predictive accuracy (Shabani, 2018). Strengthening SDM's credibility requires transparency, sensitivity analyses and recognition of model limitations. An adaptive management framework requires an iterative approach, continuous monitoring and context-specific planning to ensure effective conservation outcomes. Integrating social and economic considerations, promoting policy incorporation and refining species modelling techniques further enhance conservation strategies (Benson & Stephenson, 2018; Williams & Brown, 2014).

Limitations of SDMs depend on factors like data quality, spatial resolution and assumptions. Addressing biases through validation and incorporating relevant environmental factors is crucial for developing actionable conservation plans based on SDMs. Enhanced data collection and thorough validation with independent datasets improve model reliability and applicability (Baker *et al.,* 2024). Similarly, ensemble modelling techniques reduce uncertainty by combining predictions from multiple model simulations, enhancing overall reliability and accuracy (Maher *et al.,* 2021).

Future studies should integrate land-use change, forest fragmentation and anthropogenic disturbances with topo-climatic variables to better evaluate the long-term habitat stability of *C. deodara* in northern Pakistan. Ensemble and machine learning approaches using high-resolution environmental datasets could reduce prediction uncertainty and improve modelling reliability in complex mountainous landscapes (Allan *et al.,* 2018; Benson & Stephenson, 2018; Bishop *et al.,* 2021; Abbas *et al.,* 2023). The strong influence of Topographic Wetness Index and Hillshade observed in this study highlighted the need for field-based investigations on soil moisture availability, slope exposure and regeneration dynamics across different elevational zones. Long-term ecological monitoring in projected future suitable areas, in GB, upper KPK and AJK, would help validate predicted distribution shifts under changing climate conditions. Incorporating remote sensing datasets, species interactions and ecosystem-level processes may further improve the ecological interpretation of SDMs.

Conclusion

This study assessed the present and future habitat suitability of *C. deodara* in northern Pakistan using species distribution modelling. This research represents one of the first integrated habitat suitability assessments of *C. deodara* in northern Pakistan that combines climatic, topographic and hydrological variables with future climate projections. It was concluded that habitat suitability is strongly influenced by temperature variability, precipitation patterns and terrain-related moisture conditions. The inclusion of topographic and hydrological variables improved the ecological interpretation of habitat suitability, particularly in the complex mountainous landscapes of the Himalaya, Hindukush and Karakoram regions. Areas within KPK, GB and AJK were identified as the main suitable habitats for *C. deodara* under current conditions. Future climate projections indicated shifts in habitat distribution, with some higher elevation regions becoming more suitable under moderate warming, while prolonged warming under extreme climate scenarios may reduce habitat stability in several existing forest zones. These projected changes suggest that future conservation planning for *C. deodara* should account for both climatic trends and local environmental conditions. The findings of this study provide a useful basis for forest management and conservation planning in northern Pakistan. Regions projected to remain climatically suitable, particularly in GB, upper KPK and AJK, should be prioritized for conservation, assisted regeneration and reforestation of *C. deodara*. Protecting natural moisture regimes, reducing forest degradation and controlling unsustainable land-use activities will be important for long-term population stability. Continuous ecological monitoring and integration of land-use and high-resolution environmental data may further improve adaptive management and future habitat predictions in mountainous ecosystems.

Acknowledgements

The authors thank IDEA WILD for partial financial support of this study.

Competing Interests: The authors declare no competing interests.

Author's Contribution: R.W.A.K. (Author 1); R.W.A.K. (Author 2).; H.S.; M.E.U.I.D.; and T.S.U. contributed to the conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing-original draft preparation, writing-review and editing, and visualization. R.W.A.K. (Author 1) contributed to supervision, project administration, and funding acquisition. H.S. contributed to supervision. All authors have read and agreed to the published version of the manuscript. All authors have reviewed and approved the final version of the manuscript.

References

Abbas, S., F.M. Qamer, H. Ali, M. Usman, A. Ahmad, A. Salman and A.M. Akhter. 2023. Monitoring of large-scale forest restoration: Evidence of vegetation recovery and reversing chronic ecosystem degradation in the mountain region of Pakistan. *Ecol. Inform.*, 77: 102277.

Abrha, H., S. Dodiomon, V. Ongoma, H. Hagos, E. Birhane, G. Gebresamuel and A. Manaye. 2024. Response of plant species to impact of climate change in Hugumbrda Grat-Kahsu forest, Tigray, Ethiopia: Implications for domestication and climate change mitigation. *Trees For. People*, 15: 100487.

Ahmad, A., M. Amir, A. Mannan, S. Saeed, S. Shah, S. Ullah, R. Uddin and Q. Liu. 2018. The carbon sinks and mitigation potential of deodar (*Cedrus deodara*) forest ecosystem at different altitude in Kumrat Valley, Pakistan. *Open J. For.*, 8(4): 553.

Ahmad, A., S.M. Nizami, K.B. Marwat and J.U.M.A. Muhammad. 2015. Annual accumulation of carbon in the coniferous forest of Dir Kohistan: An inventory based estimate. *Pak. J. Bot.*, 47(SI): 115-118.

Ahmed, M., K. Nazim, M.F. Siddiqui, M. Wahab, N. Khan, M.U. Khan and S.S. Hussain. 2010. Community description of deodar forests from Himalayan range of Pakistan. *Pak. J. Bot.*, 42(5): 3091-3102.

Ahmed, M., S.S. Shaukat and M.F. Siddiqui. 2011. A multivariate analysis of the vegetation of *Cedrus deodara* forests in Hindu Kush and Himalayan ranges of Pakistan: Evaluating the structure and dynamics. *Turk. J. Bot.*, 35(4): 419-438.

Ali, A., M. Iftikhar, S. Ahmad, S. Muhammad and A. Khan. 2016. Development of allometric equation for biomass estimation of *Cedrus deodara* in dry temperate forests of Northern Pakistan. *J. Biodivers. Environ. Sci.*, 9(2): 43-50.

Ali, F., N. Khan, A.M. Khan, K. Ali and F. Abbas. 2023. Species distribution modelling of *Monotheca buxifolia* (Falc.) A. DC.: Present distribution and impacts of potential climate change. *Heliyon*, 9(2).

Ali, H., J. Din, U. Bosso, L. Hameed, S. Kabir, M. Younas, M. and M. A. Nawaz, 2021. Expanding or shrinking? Range shifts in wild ungulates under climate change in Pamir-Karakoram mountains, Pakistan. *Plos One*, 16(12): e0260031.

Allan, B.M., D.G. Nimmo, D. Ierodiaconou, J. VanDerWal, L.P. Koh and E.G. Ritchie. 2018. Futurecasting ecological research: The rise of technoecology. *Ecosphere*, 9(5): e02163.

Anonymous. 2025. Global Biodiversity Information Facility (GBIF) home page. Available at: https://www.gbif.org (Accessed 20 February 2025).

Ansari, L., W. Ahmad, A. Saleem, M. Imran, K. Malik, I. Hussain, H. Tariq and M. Munir. 2022. Forest cover change and climate variation in subtropical chir pine forests of Murree through GIS. *Forests*, 13(10): 1576.

Baker, D.J., I.M. Maclean and K.J. Gaston. 2024. Effective strategies for correcting spatial sampling bias in species distribution models without independent test data. *Divers. Distrib.*, 30(3): e13802.

Balu, A., S. Ramasamy and G. Sankar. 2023. Assessment of climate change impact on hydrological components of Ponnaiyar river basin, Tamil Nadu using CMIP6 models. *J. Water Clim. Change*, 14(3): 730-747.

Beck, H.E., E.F. Wood, T.R. McVicar, M. Zambrano-Bigiarini, C. Alvarez-Garreton and O.M. Baez-Villanueva. 2020. Bias correction of global high-resolution precipitation climatologies using streamflow observations from 9372 catchments. *J. Climate*, 33(4): 1299-1315.

Benson, A.J. and R.L. Stephenson. 2018. Options for integrating ecological, economic and social objectives in evaluation and management of fisheries. *Fish Fish.*, 19(1): 40-56.

Bhattacharyya, A., R. Dhyani, R. Joshi, M. Shekhar, J.C. Kuniyal, P.S. Ranhotra and S.P. Singh. 2023. Is survival of Himalayan cedar (*Cedrus deodara*) threatened? An evaluation based on predicted scenarios of its growth trend under future climate change. *Sci. Total Environ.*, 882: 163630.

Bishop, A.P., G. Amatulli, C. Hyseni, E. Pless, R. Bateta, W.A. Okeyo, P.O. Mireji, S. Okoth, I. Malele, G. Murilla, S. Aksoy, A. Caccone and N.P. Saarman. 2021. A machine learning approach to integrating genetic and ecological data in tsetse flies (*Glossina pallidipes*) for spatially explicit vector control planning. *Evol. Appl.*, 14(7): 1762-1777.

Bisht, A., S. Jain, A. Misra, J. Dwivedi, S. Paliwal and S. Sharma. 2021. *Cedrus deodara* (Roxb. ex D. Don) G. Don: A review of traditional use, phytochemical composition and pharmacology. *J. Ethnopharmacol.*, 279: 114361.

Bouahmed, A., F. Vessella, B. Schirone, F. Krouchi and A. Derridj. 2019. Modeling *Cedrus atlantica* potential distribution in North Africa across time: New putative glacial refugia and future range shifts under climate change. *Reg. Environ. Change*, 19(6): 1667-1682.

Chaudhary, A.K., S. Ahmad and A. Mazumder. 2011. *Cedrus deodara* (Roxb.) Loud.: A review on its ethnobotany, phytochemical and pharmacological profile. *Pharmacogn. J.*, 3(23): 12-17.

Chaudhry, Q.U.Z. 2017. Climate change profile of Pakistan. Asian Development Bank.

Chen, K., B. Wang, C. Chen and G. Zhou. 2022. MaxEnt modeling to predict the current and future distribution of *Pomatosace filicula* under climate change scenarios on the Qinghai–Tibet plateau. *Plants*, 11(5): 670.

Debebe, B., F. Senbeta, E. Teferi, D. Diriba and D. Teketay. 2023. Analysis of forest cover change and its drivers in biodiversity hotspot areas of the Semien Mountains National Park, northwest Ethiopia. *Sustainability*, 15(4): 3001.

Dormann, C.F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J.R.G. Marquéz, B. Gruber, B. Lafourcade, P.J. Leitão, T. Münkemüller, C. McClean, P.E. Osborne, B. Reineking, B. Schröder, A.K. Skidmore, D. Zurell and S. Lautenbach. 2013. Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, 36(1): 27-46.

Dunne, J.P., L.W. Horowitz, A.J. Adcroft, P. Ginoux, I.M. Held, J.G. John, J.P. Krasting, S. Malyshev, V. Naik, F. Paulot, E. Shevliakova, C.A. Stock, N. Zadeh, V. Balaji, C. Blanton, K.A. Dunne, C. Dupuis, J. Durachta, R. Dussin, P.P.G. Gauthier, S.M. Griffies, H. Guo, R.W. Hallberg, M. Harrison, J. He, W. Hurlin, C. McHugh, R. Menzel, P.C.D. Milly, S. Nikonov, D.J. Paynter, J. Ploshay, A. Radhakrishnan, K. Rand, B.G. Reichl, T. Robinson, D.M. Schwarzkopf, L.T. Sentman, S. Underwood, H.

Vahlenkamp, M. Winton, A.T. Wittenberg, B. Wyman, Y. Zeng and M. Zhao. 2020. The GFDL Earth System Model version 4.1 (GFDL-ESM 4.1): Overall coupled model description and simulation characteristics. *J. Adv. Model. Earth Syst.*, 12(11): e2019MS002015.

Durrani, M.A., R. Raza, M. Shakil, S. Sabir and M. Danish. 2024. Tree species migration to north and expansion in their habitat under future climate: An analysis of eight tree species Khyber Pakhtunkhwa, Pakistan. *J. Ecol. Environ.*, 48: 10.

Fahad, S. and J. Wang. 2020. Climate change, vulnerability and its impacts in rural Pakistan: A review. *Environ. Sci. Pollut. Res.*, 27: 1334-1338.

Fick, S.E. and R.J. Hijmans. 2017. WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. *Int. J. Climatol.*, 37(12): 4302-4315.

Gacche, R.N. and N.A. Dhole. 2006. Antioxidant and possible anti-inflammatory potential of selected medicinal plants prescribed in the Indian traditional system of medicine. *Pharm. Biol.*, 44(5): 389-395.

Gilani, H., M.A. Goheer, H. Ahmad and K. Hussain. 2020. Under predicted climate change: Distribution and ecological niche modelling of six native tree species in Gilgit-Baltistan, Pakistan. *Ecol. Indic.*, 111: 106049.

Gonzalez-Aragon, D., M.M. Rivadeneira, C. Lara, F.I. Torres, J.A. Vásquez and B.R. Broitman. 2024. A species distribution model of the giant kelp *Macrocystis pyrifera*: Worldwide changes and a focus on the southeast Pacific. *Ecol. Evol.*, 14(3): e10901.

Gu, Z., L. Gu, R. Eils, M. Schlesner and B. Brors. 2014. circlize implements and enhances circular visualization in R. *Bioinformatics*, 30(19): 2811-2812.

Hayat, W., S. Khan, A. Iqbal, S. Ahmad and A.M. Abbasi. 2021. Protection is better than management to maintain tree species: A case study of lesser-Himalayan moist-temperate forests of Pakistan. *Trees For. People*, 6: 100149.

Higgins, S.I., T. Conradi, S. Ongole, J. Turpie, J. Weiss and U. Eggli. 2023. Changes in how climate forces the vegetation of southern Africa. *Ecosystems*, 26(8): 1716-1733.

Hijmans, R. 2025. terra: Spatial data analysis. R package version 1.8-21. Available at: https://CRAN.R-project.org/package=terra

Hijmans, R., S. Phillips, J. Leathwick and J. Elith. 2024. dismo: Species distribution modeling. R package version 1.3-16. Available at: https://CRAN.R-project.org/package=dismo

Huang, T., T. Yang, K. Wang and W. Huang. 2024. Assessing the current and future potential distribution of *Solanum rostratum* Dunal in China using multisource remote sensing data and principal component analysis. *Remote Sens.*, 16(2): 271.

Karger, D.N., O. Conrad, J. Böhner, T. Kawohl, H. Kreft and R.W. Soria-Auza. 2021. Climatologies at high resolution for the earth's land surface areas. *EnviDat*. https://doi.org/10.16904/envidat.228.v2.1.

Karger, D.N., O. Conrad, J. Böhner, T. Kawohl, H. Kreft and R.W. Soria-Auza. 2017. Climatologies at high resolution for the earth's land surface areas. *Sci. Data*, 4: 170122.

Kassa, K., G. Gebeyehu, T. Bekele and S. Abebe. 2023. Rehabilitation options for degraded secondary forests in Adiyo district of Kaffa zone, southwest Ethiopia. *Trees For. People*, 12: 100394.

Khan, N., M. Ahmed and S.S. Shaukat. 2013. Climatic signal in tree-ring chronologies of *Cedrus deodara* from Chitral Hindukush range of Pakistan. *Geochronometria*, 40: 195-207.

Kim, J.Y., G.Y. Kim, Y. Do, H.S. Park and G.J. Joo. 2018. Relative importance of hydrological variables in predicting the habitat suitability of *Euryale ferox* Salisb. *J. Plant Ecol.*, 11(2): 169-179.

Kumar, A. and A. Pandey. 2024. A bibliometric analysis of 100 years of research on Himalayan cedar: Research trends, gaps and future implications. *Front. For. Glob. Change*, 7: 1485083.

Kumar, S. and V.P. Khanduri. 2024. Impact of climate change on the Himalayan alpine treeline vegetation. *Heliyon*, 10(23): e40797.

Latif, M., F.S. Syed and A. Hannachi. 2017. Rainfall trends in the South Asian summer monsoon and its related large-scale dynamics with focus over Pakistan. *Clim. Dyn.*, 48: 3565-3581.

Ma, J., J. Li, W. Wu and J. Liu. 2023. Global forest fragmentation change from 2000 to 2020. *Nat. Commun.*, 14(1): 3752.

Maher, N., S. Milinski and R. Ludwig. 2021. Large ensemble climate model simulations: Introduction, overview and future prospects for utilising multiple types of large ensemble. *Earth Syst. Dyn.*, 12(2): 401-418.

Malik, S.M., H. Awan and N. Khan. 2012. Mapping vulnerability to climate change and its repercussions on human health in Pakistan. *Glob. Health*, 8: 31.

Merow, C., J.M. Allen, M. Aiello-Lammens and J.A. Silander Jr. 2016. Improving niche and range estimates with Maxent and point process models by integrating spatially explicit information. *Glob. Ecol. Biogeogr.*, 25(8): 1022-1036.

Monks, A., D. Scudiero, P. Skehan, R. Shoemaker, K. Paull, D. Vistica, C. Hose, J. Langley, P. Cronise, A. Vaigro-Wolff, M. Gray-Goodrich, H. Campbell, J. Mayo and M. Boyd. 1991. Feasibility of a high-flux anticancer drug screen using a diverse panel of cultured human tumor cell lines. *J. Natl. Cancer Inst.*, 83(11): 757-766.

Moulatlet, G.M., C.D. Rennó, F.O.G. Figueiredo, K. Ruokolainen, L. Banon, T. Emilio, H. Balslev and H. Tuomisto. 2022. The role of topographic-derived hydrological variables in explaining plant species distributions in Amazonia. *Acta Amazon.*, 52(3): 218-228.

Muscatello, A., J. Elith and H. Kujala. 2021. How decisions about fitting species distribution models affect conservation outcomes. *Conserv. Biol.*, 35(4): 1309-1320.

Naikoo, M.I., M.I. Dar, F.A. Khan, A.A. Ansari, F.R. Rehman and F.N. Nousheen. 2017. Gymnosperm diversity of the Kashmir Himalayas. In: *Plant Biodiversity: Monitoring, Assessment and Conservation*. CABI, Wallingford, UK, pp. 228-238.

Nasir, G.M. and H. Shah. 2014. Variation in density with respect to growth rate in deodar (*Cedrus deodara*) wood. *Pak. J. For.*, 64(2): 19-24.

Negi, G.C.S. 2022. Trees, forests and people: The central Himalayan case of forest ecosystem services. *Trees For. People*, 8: 100222.

Nirala, D., U.B. Pratap and D.R. Bhardwaj. 2022. Altitudinal variation on physiological attributes of *Cedrus deodara* (Roxb.) G. Don in north-western Himalaya. *Pharma Innov. J.*, 11(12): 3319-3323.

Pandey, R., M. Rawat, A. Pathak, D. Mehta, N. Bala, I.D. Bhatt and R.K. Chaturvedi. 2023. Identification of functional traits responsible for environmental vulnerability of *Cedrus deodara* in temperate forests of western Himalaya. *Ecol. Indic.*, 157: 111302.

Pathak, H., S. Pathania, S. Mehta and R. Sharma. 2023. *Cedrus deodara* (Roxb.): A review on the recent update on its pharmacological and phytochemical profile. *RPS Pharm. Pharmacol. Rep.*, 2(3): rqad026.

Pearson, R.G., C.J. Raxworthy, M. Nakamura and A.T. Peterson. 2007. Predicting species distributions from small numbers of occurrence records: A test case using cryptic geckos in Madagascar. *J. Biogeogr.*, 34(1): 102-117.

R Core Team. 2025. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. Available at: https://www.R-project.org.

Rahman, I.U., R.E. Hart, A. Afzal, Z. Iqbal, R.W. Bussmann, F. Ijaz, M.A. Khan, H. Ali, S.U. Rahman, A. Hashem, E. Fathi, A. Sher and E.S. Calixto. 2023. Vegetation–environment interactions: Plant species distribution and community assembly in mixed coniferous forests of northwestern Himalayas. *Sci. Rep.*, 13(1): 1-16.

Rana, D., K.S. Kapoor, S.S. Samant and A. Bhatt. 2020. Plant species conservation priority index for preparing management strategies: A case study from the western Himalayas of India. *Small Scale For.*, 19: 461-481.

Rasheed, F., S. Yaqoob and A.H. Ahmad. 2017. Forest types of Pakistan. In: *Textbook of Applied Forestry*. Available at: http://onlinebooks.uaf.edu.pk/ChapterView.aspx?ChapId=217

Sajad, S., J. Jawad and I. Haq. 2021. Dendrochronological study of *Cedrus deodara* grown at Kumrat valley Dir Upper KPK, Pakistan: Evaluation of tree age and increment based on increment core. *J. Ilmu Pertan. Indones.*, 26(2): 201-208.

Shabani, F. 2018. Assessing accuracy methods of species distribution models: AUC, specificity, sensitivity and the true skill statistic. *Glob. J. Hum. Soc. Sci.*, 18(B1): 7-18.

Shah, S.K., U. Pandey and N. Mehrotra. 2018. Precipitation reconstruction for the Lidder Valley, Kashmir Himalaya using tree-rings of *Cedrus deodara*. *Int. J. Climatol.*, 38: e758-e773.

Sheikh, M.A., M. Kumar, N.P. Todaria, J.A. Bhat, A. Kumar and R. Pandey. 2021. Contribution of *Cedrus deodara* forests for climate mitigation along altitudinal gradient in Garhwal Himalaya, India. *Mitig. Adapt. Strateg. Glob. Change*, 26: 1-19.

Sher, H., A. Ali, H. Sher, R.W. Bussmann, I.U. Rahman, H. Ullah, A. Ali and Z. Ullah. 2023. Sustainability and socio-economic impacts of plant resources utilization in Valley Lalku, District Swat, Pakistan. *Ethnobot. Res. Appl.*, 26: 1-18.

Thakur, K.K., P. Bhat, A. Kumar, G. Ravikanth and P. Saikia. 2021. Distribution mapping of *Bauhinia vahlii* Wight & Arn. in India using ecological niche modelling. *Trop. Ecol.*, 63(2): 286-299.

Trew, B.T. and I.M. Maclean. 2021. Vulnerability of global biodiversity hotspots to climate change. *Glob. Ecol. Biogeogr.*, 30(4): 768-783.

Wani, N.R., K.N. Qaisar and P.A. Khan. 2014. Biomass, carbon stock and carbon dioxide mitigation potential of *Cedrus deodara* under temperate conditions of Kashmir. *Can. J. Pure Appl. Sci.*, 8: 2677-2684.

Warren, D.L., N.J. Matzke and T.L. Iglesias. 2020. Evaluating presence-only species distribution models with discrimination accuracy is uninformative for many applications. *J. Biogeogr.*, 47(1): 167-180.

Wei, T. and V. Simko. 2024. corrplot: Visualization of a correlation matrix. R package version 0.95. Available at: https://github.com/taiyun/corrplot

Williams, B.K. and E.D. Brown. 2014. Adaptive management: From more talk to real action. *Environ. Manage.*, 53: 465-479.

Xiao, S., S. Li, X. Wang, L. Chen and T. Su. 2022. *Cedrus* distribution change: Past, present and future. *Ecol. Indic.*, 142: 109159.

Yadava, A.K., K.G. Misra, V. Singh, S. Misra, Y.K. Sharma and B.S. Kotlia. 2021. 244-year long tree-ring based drought records from Uttarakhand, western Himalaya, India. *Quat. Int.*, 599-600: 128-137.

Zaman, T., M.S. Syed, S. Isfaq and M.S. Khan. 2018. Biological activities of stem, leaves and essential oil of *Cedrus deodara* from district Poonch, Rawalakot Azad Kashmir, Pakistan. *Turk. J. Agric. Food Sci. Technol.*, 6(9): 1114-1119.

Zeb, A., A. Hamann, G.W. Armstrong and D. Acuna-Castellanos. 2019. Identifying local actors of deforestation and forest degradation in the Kalasha valleys of Pakistan. *For. Policy Econ.*, 104: 56-64.

Zellmer, A.J., J.T. Claisse, C.M. Williams, S. Schwab and D.J. Pondella. 2019. Predicting optimal sites for ecosystem restoration using stacked-species distribution modeling. *Front. Mar. Sci.*, 6: 3.

Zhang, J.M., X.F. Shi and B. Fan. 2009. Chemical composition and pharmacological activities of *Cedrus deodara*. *Chin. Tradit. Plant Med.*, 31: 928-933.

Zhao, M., J.C. Golaz, I.M. Held, H. Guo, V. Balaji and R. Benson. 2018. The GFDL global atmosphere and land model AM4.0/LM4.0: 1. Simulation characteristics with prescribed SSTs. *J. Adv. Model. Earth Syst.*, 10(3): 691-734.

Zingraff-Hamed, A., M. Noack, S. Greulich, K. Schwarzwälder, S. Pauleit and K.M. Wantzen. 2018. Model-based evaluation of the effects of river discharge modulations on physical fish habitat quality. *Water*, 10(4): 374.