Under predicted climate change: Distribution and ecological niche modelling of six native tree species in Gilgit-Baltistan, Pakistan

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Summary

Based on bioclimatic variables and 440 samples of six native trees species (*Abies pindrow*, *Betula utilis, Cedrus deodara, Picea smithiana, Pinus wallichiana* and *Quercus ilex)* collected through field surveys data, the study presents the tree species distribution or habitat suitability maps in Gilgit-Baltistan, Pakistan at 1 km spatial resolution. Multicollinearity test was applied on different bioclimatic variables and topographical conditions, and the results were then employed in the Maximum Entropy (MaxEnt) model to produce current, RCP4.5 and RCP8.5 climate-change scenarios by 2050 tree species spatial distribution. The jackknife test was carried out to depict the importance of variables with highest gain and found that overall elevation, precipitation, and temperature are the factors with the highest gain. The results of MaxEnt model for each tree species were satisfactory, with a ROC (receiver operating characteristic) curve (AUC) training and testing values greater than 0.9 and 0.84 respectively. Based on 10-percentile training presence threshold-dependent values, the overall accuracy of True Skill Statistics (TSS) was more than 80%. The maximum area coverage of all tree species existed under “inadmissible natural surroundings (0-0.2 probability)” and least area fallen under “exceptionally appropriate environment (0.6-0.7 probability)” to “profoundly reasonable living space (0.7-1.0 probability)”.

List of acronyms

AI	Aridity Index
AUC	Area Under Curve
BCC-CSM	Beijing Climate Centre - Climate System Modelling
DEM	Digital Elevation Model
GAM	Generalized Additive Model
GBM	Generalized Boosted Model
GLM	Generalized Linear Model
HKH	Hindu Kush Himalayan
MaxEnt	Maximum Entropy
masl	meter above sea level
MARS	Multivariate Adaptive Regression Splines
PET	Potential Evapotranspiration
RCP	Representative Concentration Pathway
RF	Random Forest
ROC	Receiver Operating Characteristic curve
TRI	Terrain Roughness Index
TSS	True Skill Statistics

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1. Introduction

The healthy and well-managed forests are instrumental in fighting against threatening forces, e.g., air pollution, pests, wildfires, droughts, floods, windstorms, and invasive alien species. To prevent from threading forces and mitigate the impacts of climate change on woodland biological communities. It can successfully target conservation strategies by demonstrating species distribution to distinguish ranges where species occurred or likely to be presented (Gotelli and Colwell, 2001; Qin et al., 2017). In the last couple of years, the development of computer technologies, mapping algorithms/models, and field data collection techniques have achieved logical acknowledgments towards permitting the production of spatially explicit species distribution outputs (Porfirio et al., 2014).

The species distribution and prediction models and tools are increasingly becoming popular in ecology and widely being used to map the potential distribution of flora and fauna species. GIS-based species distribution models combine species occurrence with multiple environmental layers (bioclimatic and/or remote sensing and/or topography) to predict, estimate and map the expected presence of species over the larger area (Adhikari et al., 2012; Brown, 2014; Cánovas et al., 2016; Khanum et al., 2013; Tripathi et al., 2017; Yang et al., 2013).

Several species ecological niche, habitat suitability and distribution models (e.g., Generalized linear model (GLM), Generalized additive model (GAM), Multivariate adaptive regression splines (MARS), Generalized boosted model (GBM), Random Forest (RF), Maximum Entropy (MaxEnt), etc.) are available, But the outputs of models depend on the nature, complexity, and accuracy of adopted model and quality of the selected environmental layers with the availability of sufficient, dependable species occurrence data as model inputs (Naimi and Araújo, 2016; Ranjitkar et al., 2016, 2014a). The results of species distribution models are valuable instruments on providing information to decision makers and practitioners to take necessary action towards the species conservation and their habitats under a rapidly changing climate. Due to the challenges of fieldwork data collection, most of the species distributions and ecological niche modelling studies rely on presence-only data. It often retrieved from databases of natural history, museums, literature review and herbaria, which evident from the number of researchers, examined and recorded from different procedures, intensities and periods (Ashraf et al., 2016; Bobrowski et al., 2017). For the species distribution modelling, presence-absence occurrence data (direct measurements from the field) produces less uncertainty as compared to the presence-only occurrence data (Bobrowski et al., 2017; Elith et al., 2006).

The MaxEnt species distribution or ecological niche model (Phillips et al., 2004; Phillips and Dudík, 2008) assess the maximum entropy based distribution, to find most of the species distribution spread closest to reality (Ashraf et al., 2016; Fourcade et al., 2014; Merow et al., 2013; Qin et al., 2017; Saatchi et al., 2011).

Number of species distribution, suitability and projection modelling and mapping studies were carried out across the Hindu Kush Himalayan (HKH) region; *Taxus/*Yews (Poudel et al., 2012), medicinal plant *Justicia adhatoda L* (Yang et al., 2013), *Rhododendron* tree species (Ranjitkar et al., 2014a), Nyctaginaceae species (Ranjitkar et al., 2014b), Banana and Coffee (Ranjitkar et al., 2016), Liliaceae (Rana et al., 2017), *Olea* species (Ashraf et al., 2016), *Betula utilis* (Bobrowski et al., 2017). Based on the literature review, only two studies were conducted on tree species i.e. *Rhododendrons* (*R. delavayi* and *R. arboreum*) (Ranjitkar et al., 2014a) and *Betula utilis* (Bobrowski et al., 2017) over HKH region with limited ground observations.

With this background, the overall objective of this study is to combine total 440 field measures of six native tree species (*Abies pindrow*, *Betula utilis, Cedrus deodara, Picea smithiana, Pinus wallichiana* and *Quercus ilex)* occurrence information with bioclimatic and topographical derived variables in MaxEnt model for the potential distribution and ecological niche modelling across Gilgit-Baltistan. Apart from present tree species distribution, two Representative Concentration Pathway (RCP) trajectories (RCP4.5 and RCP8.5) of the BCC-CSM1.1 model was used as the future (2050) projection of six native tree species distribution. The government of Pakistan has banned chopping off, transportation, and export of these selected tree species (Faiza et al., 2017). The spatially explicit seminal tree species distribution data is vital for Gilgit-Baltistan, especially for forest ecosystem management plans, forests environmental impact assessment studies, understanding and studying shifting treelines and performance evaluation of forest regimes (e.g., community, leasehold, private, government, etc.).

2. Study area

Gilgit-Baltistan (formerly Northern Areas) is an administrative unit (divided into ten districts) in the extreme north of Pakistan (Figure 1). It covers an area of 72,971 km^2 (Kazim et al., 2015), including 1,582 km^2 of forest (Qamer et al., 2016) within the high mountain ranges of the Karakorum, Himalayas, Hindu Kush, and Pamir. Most of the land lies at and above 4,500 masl. The climatic conditions vary widely, ranging from monsoon-influenced moist temperate in the western Himalayas, to arid and semi-arid cold desert in the northern Karakoram and Hindu Kush. Below 3,000 masl, precipitation is low, rarely exceeding 200 mm annually, but there is a strong gradient with elevation and at 6,000 masl, the equivalent of 2,000 mm per year falls as snow.

Temperatures in the valley bottoms can range from extremes of 40°C in summer to -10°C in winter (Akbar et al., 2011; Ismail et al., 2018; Kazim et al., 2015).

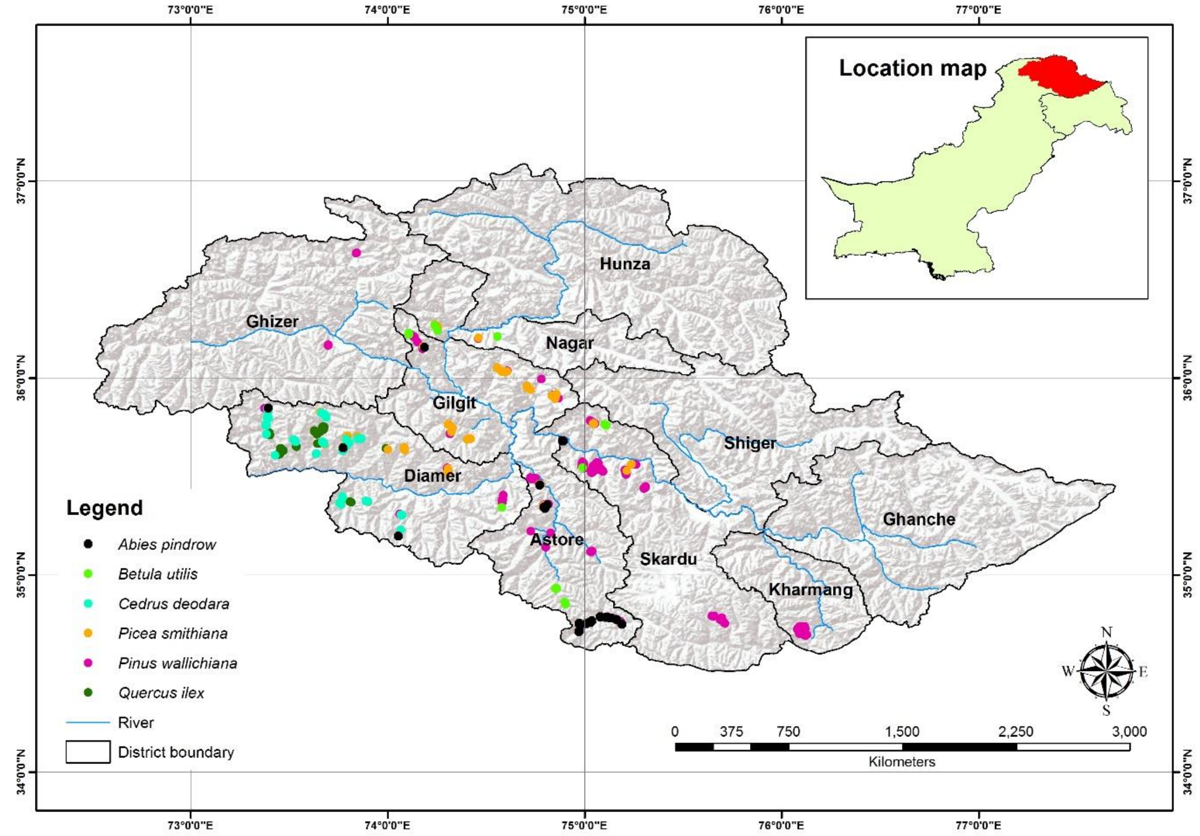

Figure 1: Study area map shows the six native trees species locations in Gilgit-Baltistan, Pakistan

3. Material

To map potential distribution of six native trees species in Gilgit-Baltistan, the datasets used in this study consist of: (1) Tree species location data, (2) Bioclimatic variables and (3) Topographical variables.

3.1. Tree species location data

From the field, well-distributed circular 556 sample plots of 1000 m^2 (0.04% of the total forest area) were measured between June to October 2015 and 2016. A slope correction factor was applied for every plot to determine the exact plot radius. Within each sample plot, a total number of tree species were recorded along with geographic coordinates and elevation values. The details of field data collection given in (Ismail et al., 2018). For this study, field-measured forest plots, only those plots were selected which contain more than 80% presence of one particular tree species. Total of 440 samples six native tree species records were used for the tree species distribution and mapping over the entire Gilgit-Baltistan (Table 1 and Figure 1). Based on the detailed forest inventory in Gilgit-Baltistan, for the tree species distribution modelling six most dominant native tree species were selected: two broadleaved (*Quercus ilex and Betula utilis) and* four coniferous (*Abies pindrow, Cedrus deodara, Picea smithiana and Pinus wallichiana)* (Annex 1).

Table 1: Selected six native trees species for distribution modelling in Gilgit-Baltistan, Pakistan

Scientific name	Local name	Tree counts	Elevation ranges (m)
Abies pindrow	Fir	34	2,500-3,500
Betula utilis	Birch	22	2,500-3,800
Cedrus deodara	Deodar	54	1,800-3,000
Picea smithiana	Spruce	68	2,300-4,000
Pinus wallichiana	Pine	222	2,200-4,000
Quercus ilex	Oak	40	1,800-3,000

3.2. Bioclimatic variables

Globally there are 21 bioclimatic variables available at 30 arc seconds (~ 1 km spatial resolution at the equator) out of which 19 bioclimatic variables was downloaded from the Chelsa-climate web portal (http://chelsa-climate.org) (Karger et al., 2016). These bioclimatic datasets consist of an average monthly temperature and precipitation for the years 1979-2013 (Karger et al., 2016). The Annual Aridity Index (AI) and Potential Evapotranspiration (PET) were acquired from the CGIAR-CSI website (http://www.cgiar-csi.org/data/global-aridity-and-pet-database) (Zomer et al., 2008) All the datasets were at 1 km spatial resolution (Annex 2).

There are four RCPs, ranging from RCP 2.6 (aggressive mitigation/lowest emissions) to RCP 8.5 (higher emission scenario). The RCP4.5 is an optimistic climate-change scenario where emissions peak around 2040, and RCP8.5 is a pessimistic climate-change scenario where emissions keep rising through the 2100 (Meinshausen et al., 2011; van Vuuren et al., 2011). Future bioclimatic variables were developed by the Beijing Climate Center, China Meteorological Administration, derived from a global circulation model: BCC-CSM1.1 (Beijing Climate Centre - Climate System Modelling 1.1). In this study, two RCPs trajectories (RCP4.5 and RCP8.5) of the BCC-CSM1.1 models were used as the future (2050) projection of six native tree species distribution.

3.3. Topographical variables

In this study, remote sensing variable at one arc second (30 m spatial resolution) Digital Elevation Model (DEM) was freely downloaded from the USGS Earth Explorer web portal (https://earthexplorer.usgs.gov/). DEM and its derived products; slope and Terrain Roughness Index (TRI) were used as independent variables in the modelling (Annex 2).

The topographical datasets were up-scaled at 1 km spatial resolution to bring spatial consistency among bioclimatic and topographic layers. All bioclimatic and topographical variable layers were clipped at the extent of Gilgit-Baltistan.

4. Methodology

To study six different native trees species potential spatial distribution in Gilgit-Baltistan, the adopted method comprised of three parts: (1) Ensemble MaxEnt model, (2) Evaluate MaxEnt model results and (3) Quantification of predicted trees species.

4.1. Ensemble MaxEnt model

The MaxEnt model combines categorical dependent variables and continuous independent biophysical variables. MaxEnt model has a unique characteristic in the categorical prediction of occurrences in relation to other common approaches (Elith et al., 2011). From MaxEnt model, the output map values range from 0 to 1 (0 least and 1 most suitable species probability pixels) (Phillips and Dudík, 2008).

Multicollinearity is a common problem, when there are high correlations among independent variables, leading to unreliable and unstable estimates of regression coefficients (O'brien, 2007). Exclusively for each tree species, a multicollinearity test was performed among 24 independent or environment variables (21 bioclimatic, and 3 topographic). The highly correlated independent variables, i.e., r ≥ 0.9 Pearson correlation coefficient (Graham, 2003) were eliminated from further MaxEnt modelling (Annex Table S3). In the MaxEnt model for trees species distribution mapping, we combined trees species location data as dependent variables and after multicollinearity test, the selected bioclimatic and topographic datasets as independent variables. To obtain, current, RCP4.5 and RCP 8.5 tree species distributions, MaxEnt model was ran independently.

4.2. Evaluate MaxEnt model

For the current, RCP4.5 and RCP8.5, initially the accuracy of the MaxEnt model was assessed by partitioning tree species presence data into training and test datasets (75% of records used to train the model and for 10-fold cross-validation 25% of records used to test the results of model). Without test data, the model employs all the input data to run the model and develop results. In the MaxEnt model parameters setting, 'random seed' were selected so that on each iteration, model takes the different set of presence records for training and testing. To improve the model's performance, 10,000 randomly distributed background points were generated (called: absence or background data).

For current, RCP4.5 and RCP8.5 climate-change scenarios by 2050, the performance of the model for each tree species was evaluated using the two different methods: 1). Area under the ROC (receiver operating characteristic) curve (AUC) and 2). Threshold-dependent True Skills Statistic (TSS), kappa statistics with overall accuracy values. Both methods were adopted for evaluation, as the number of research proposed that the AUC values are misleading the performance of predictive distribution models and reflect relative model performance (Bobrowski et al., 2017; Lobo et al., 2008).

A ROC curve is the most commonly used approach to visualize and summarize the performance of a binary classifier model. The large areas under the ROC curve indicate higher or better performance of mode (Phillips et al., 2004; Radosavljevic et al., 2014). The AUC score <0.5 indicates model discrimination, while the values ranging between 0.5-0.7 are considered low accuracy, values ranging from 0.7 to 0.9 are rated as adequate accuracy and the values >0.9 show very high accuracy of predicted output of the model (Elith et al., 2006; Manel et al., 2001; van Proosdij et al., 2016). In this study, for the evaluation of the model of each tree species probability distribution, ROC curve was acquired by plotting sensitivity versus (1-specificity) for varying probability threshold values. Within MaxEnt model, the Jackknife test allowed us the relative importance of environmental variables to identify important individual parameters for each tree species distribution map (Elith et al., 2011).

The threshold-dependent measures is an error matrix which calculates the corresponding values of the sensitivity, specificity, the overall accuracy, the Cohen's kappa statistic and TSS values. The error matrix relates subsequent observed versus predicted values. For each tree species, to evaluate the results of MaxEnt model performance, 10-percentile training presence value was taken as a threshold for calculating overall accuracy, kappa and TSS values. The kappa statistic value ranges from -1 to +1, (<1 value indicatives of a model performance which is worse than random) (Allouche et al., 2006; Bobrowski et al., 2017; Landis and Koch, 1977).

4.3. Quantification of predicted tree species

For each tree species, the predicted output of the MaxEnt model values from 0 to 1 were reclassified as suggested and adopted by Yang et al. (2013). The probability distribution were reclassified and renamed into five classes for each tree species: 1). Unsuitable (0–0.2): inadmissible natural surroundings; 2). Less suitable (0.2-0.4): scarcely reasonable living space; 3). Moderately suitable (0.4-0.6): appropriate territory; 4). Highly suitable (0.6-0.7): exceptionally appropriate environment and 5). Very highly suitable (0.7-1.0): profoundly reasonable living space. For each tree species, under each defined class the area in percentage was calculated.

5. Results

The results of six native trees species potential distribution in Gilgit-Baltistan consists of four sections: (1) Environmental variables, (2) Model calibration and evaluation, (3) Tree species distribution, and (4) Tree diversity map

5.1. Environmental variables for MaxEnt model

Based on the multicollinearity test ($r < 0.9$ Pearson correlation coefficient), 10 variables for *Abies pindrow* and *Pinus wallichiana*, 9 for *Picea smithiana,* 8 for *Betula utilis* and *Cedrus deodara*, and 7 variables for *Quercus ile* were taken as input variables in MaxEnt model.

Through multicollinearity tests among six selected tree species, twelve common variables: Bio01, Bio04, Bio05, Bio06, Bio10, Bio11, Bio12, Bio13, Bio14, Bio16, Bio17 and Bio19 and some other variables with highly correlated values ($r \geq 0.9$) were rejected as independent variables in the MaxEnt model. Similarly, among all tree species, nine shared variables: TRI, Slope, Bio08 and Bio15 and some other variables with less correlated values ($r < 0.9$) were accepted to be included in MaxEnt model (Annex Table S4).

5.2. MaxEnt model calibration and evaluation

The MaxEnt model for each tree species provided satisfactory results, with an AUC training and testing values greater than 0.9 of current, RCP4.5 and RCP8.5 tree species distribution, which were higher than random prediction AUC value, i.e. 0.5 (Table 2).

For current tree species distribution, the Jackknife test to evaluating the relative importance of environment variables for each tree species presented in Figure 2. The jackknife test of variables influence depicted overall elevation, precipitation, and temperature are examples of factors with the highest gain. The contribution of least variables varied for each tree species.

Table 2: Area under the ROC (receiver operating characteristic) curve (AUC) values achieved through MaxEnt model performance for each tree species by partitioning tree species presence-only data into training (75%) and test (25%) with standard deviation

		Abies pindrow	***Betula utilis***	***Cedrus deodara***	***Picea smithiana***	***Pinus wallichiana***	***Quercus ilex***
Current	**Training**	0.993	0.971	0.995	0.983	0.981	0.993
	Test	0.970±0.019	0.984±0.008	0.993± 0.002	0.979±0.005	0.974±0.009	0.996±0.002
RCP4.5	**Training**	0.986	0.903	0.994	0.981	0.979	0.997
	Test	0.999±0	0.896± 0.042	0.993±0.003	0.971±0.010	0.972±0.007	0.978±0.013
RCP8.5	**Training**	0.987	0.972	0.995	0.987	0.978	0.994
	Test	0.995±0.003	0.970±0.018	0.994±0.003	0.978±0.008	0.983±0.003	0.998±0.001

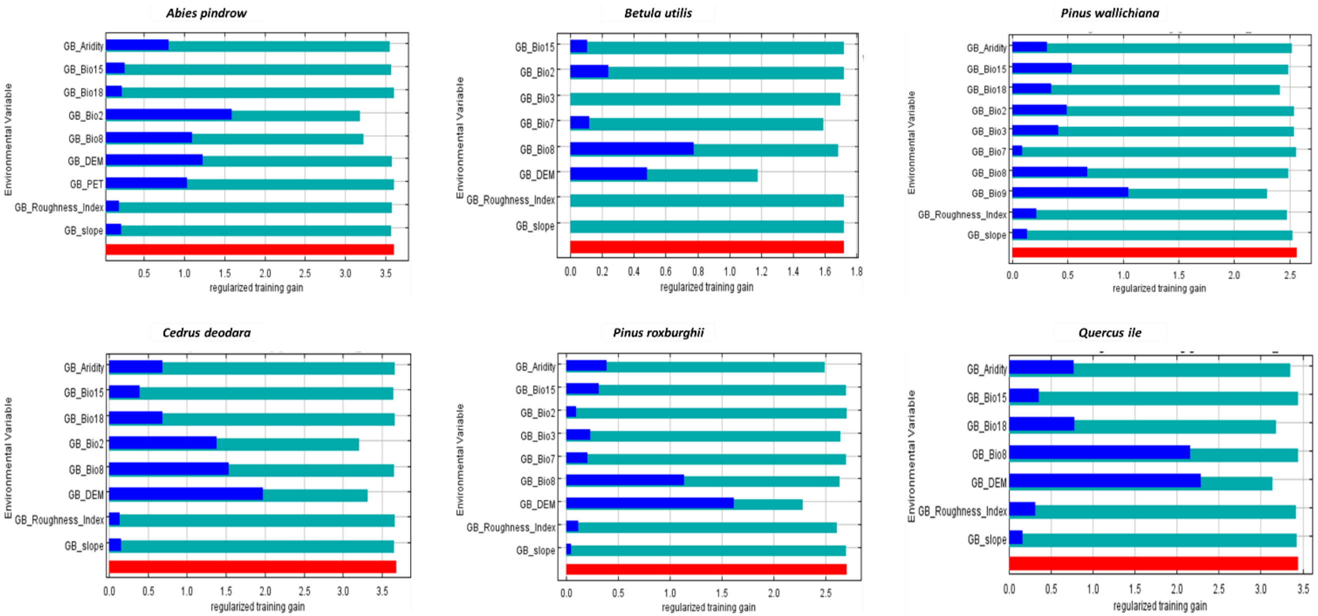

Figure 2: The Jackknife test for evaluating the relative importance of environmental variables for each tree species

For all current, RCP4.5 and RCP 8.5 tree species distribution, based on 10-percentile training presence threshold-dependent, the overall accuracy achieved more than 80%. For current tree species distribution, except for *Abies pindrow* and *Picea smithiana* tree species, TSS values attained more than 0.8. For RCP4.5 climate-change scenario by 2050, *Pinus wallichiana* attained TSS value less than 0.8 while for RCP8.5 tree species distribution, *Betula utilis*, *Cedrus deodara* and *Picea smithiana* tree species gained less than 0.8 TSS values (Table 3).

Except from *Quercus ilex* in RCP4.5, the sensitivity values achieved more than 0.5 for all tree species in current, RCP4.5 and RCP8.5 climate-change scenarios by 2050. The specificity values for all current and RCP8.5 tree species distribution obtained higher than 0.9. While in RCP4.5 tree species distribution, except *Betula utilis*, all species attained higher than 0.8 values. Except *Betula utilis* tree species distribution under RCP4.5 climate-change scenario by 2050, all the tree species obtained more than 0.9 overall accuracy (Table 3).

5.3. Tree species distribution

Based on the geographical representation of tree species distribution (Figure 3, 4 and 5), northern region of study area has inadmissible natural surroundings with distributed tree species. Most of the tree species distribution exist in the southern or at lower elevations of the study area. Based on tree species distribution, exceptionally over estimation of *Betula utilis* tree species was observed in the current distribution as well as in RCP4.5 and RCP8.5 climate-change scenario by 2050. *Cedrus deodara* and *Quercus ilex* tree species, higher concentration observed in Diamer district of Gilgit-Baltistan, Pakistan. *Picea smithiana* and *Pinus wallichiana* tree species was found well spread and controlled distribution spotted in Gilgit, Diamer, Astore, Skardu and Ghanche districts.

Based on the area (Table 4), the maximum percentage coverage area (more than 70%) of all tree species lies under “inadmissible natural surroundings (0-0.2)” and least area (less than 4%) falls under “exceptionally appropriate environment (0.6-0.7)” to “profoundly reasonable living space (0.7-1.0)”. Under the “scarcely reasonable living space (0.2-0.4)” and “appropriate territory (0.4-0.6)” categories the appearance of the all five native trees species reasonably satisfactory (Table 4).

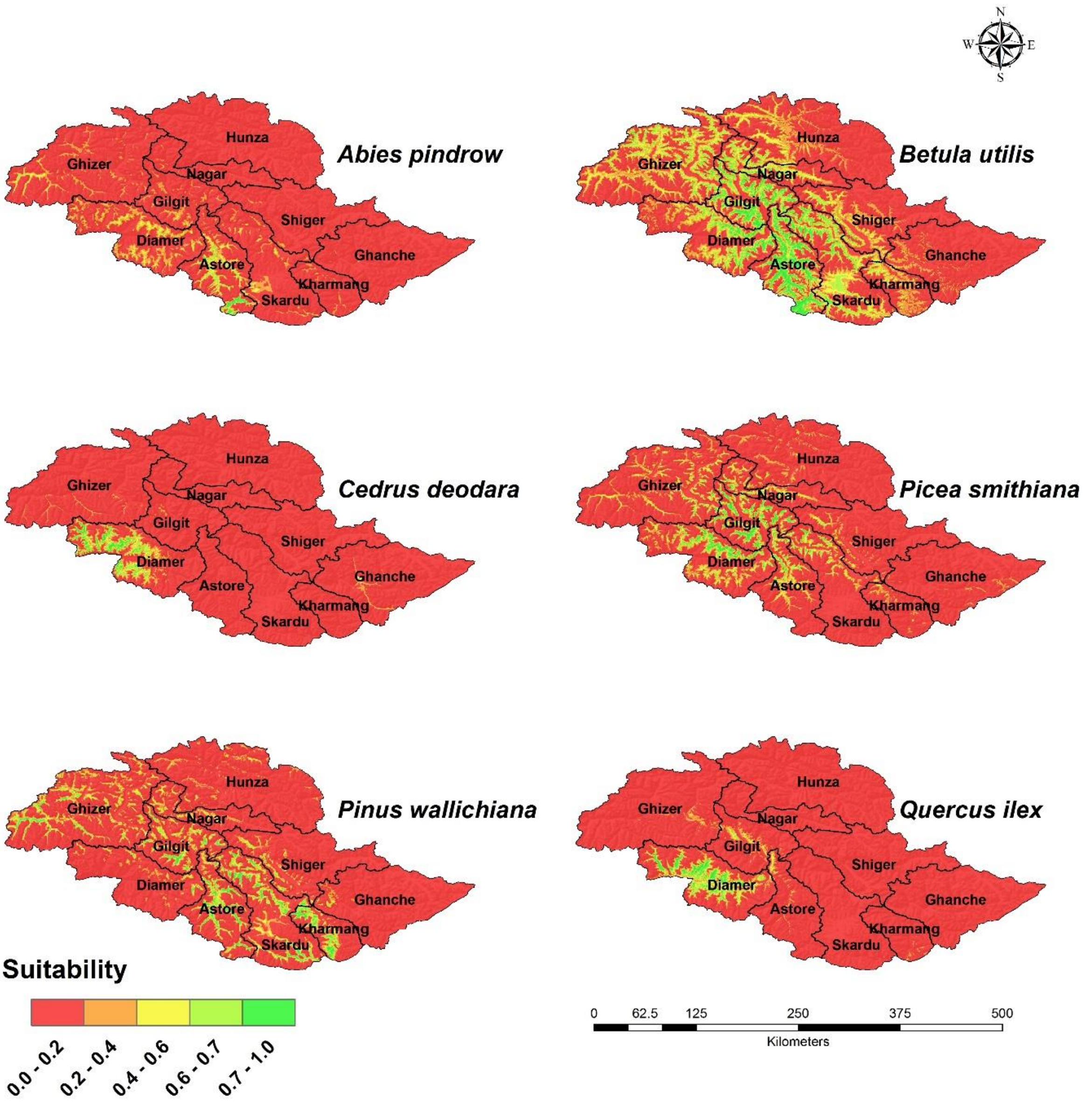

Figure 3: Current: Predicted potential distribution of six native trees species

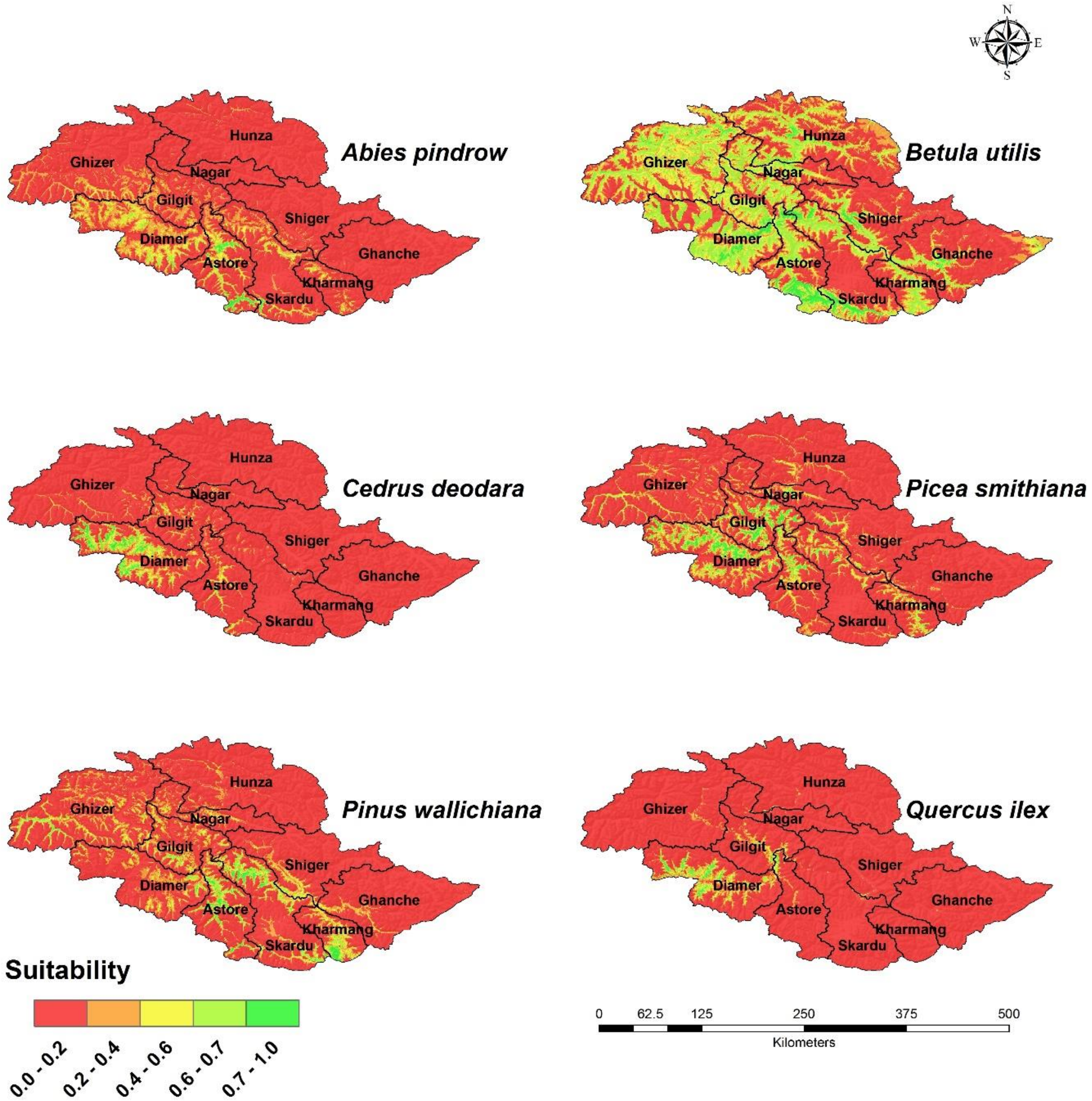

Figure 4: RCP4.8: Predicted potential distribution of six native trees species

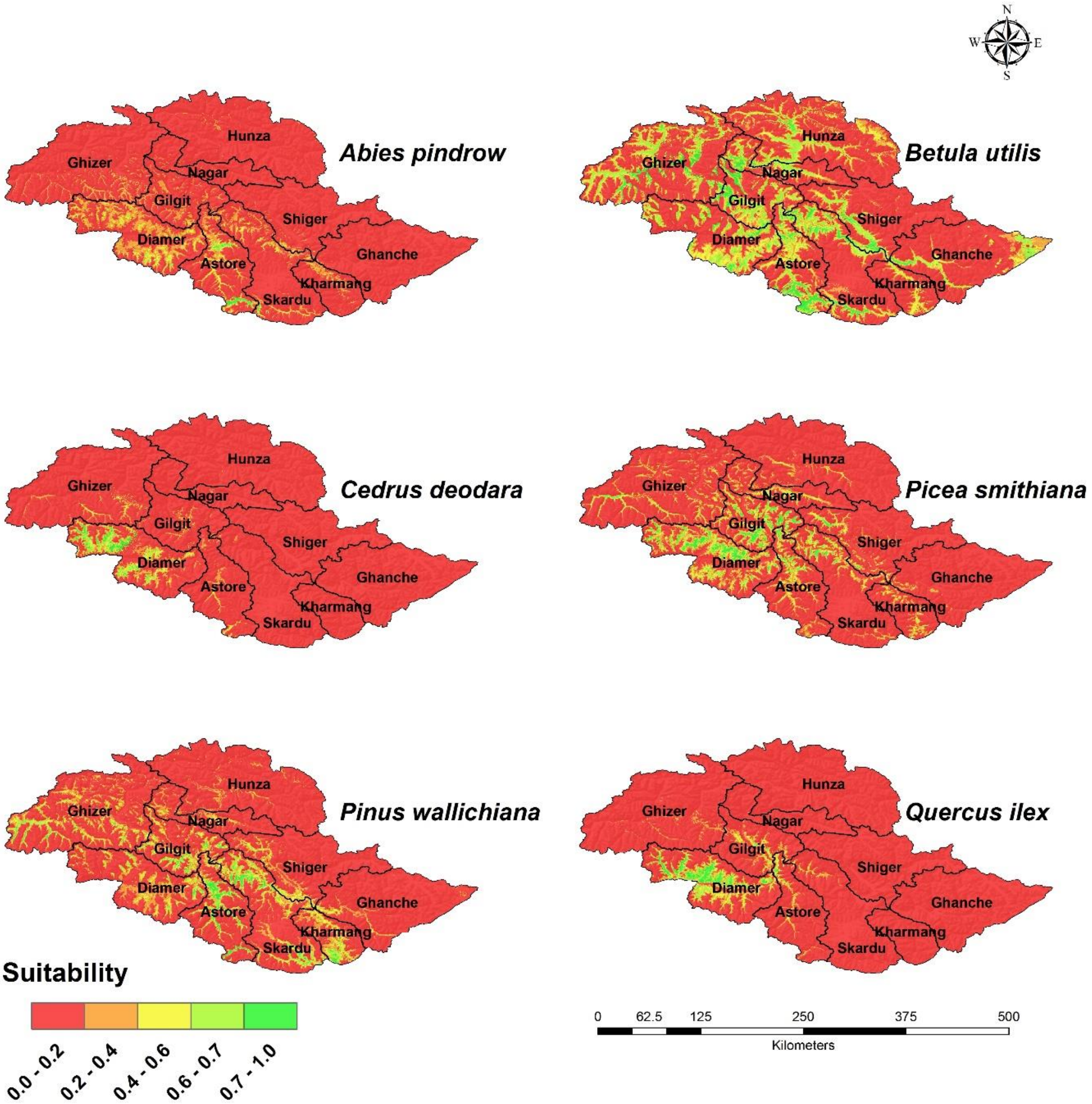

Figure 5: RCP8.5: Predicted potential distribution of six native trees species

Table 3: Evaluation results for MaxEnt Model through 10 percentile training presence - threshold-dependent True Skills Statistic (TSS), sensitivity, specificity, kappa statistics with overall accuracy values

		Abies pindrow	***Betula utilis***	***Cedrus deodara***	***Picea smithiana***	***Pinus wallichiana***	***Quercus ilex***
Current	**10 percentile training presence - Threshold-dependent**	0.01	0.44	0.39	0.29	0.26	0.28
	Sensitivity	0.67	1	0.89	0.77	0.89	1
	Specificity	0.97	0.94	0.99	0.97	0.96	0.98
	TSS	0.63	0.94	0.88	0.74	0.96	0.98
	Kappa	0.02	0.01	0.16	0.05	0.10	0.06
	Kappa maximum	0.31	0.45	0.43	0.37	0.43	0.48
	Overall accuracy	0.97	0.94	0.99	0.97	0.96	0.98
RCP4.5	**10 percentile training presence - Threshold-dependent**	0.1	0.2	0.35	0.31	0.24	0.49
	Sensitivity	1	1	0.89	0.85	0.82	0.5
	Specificity	0.94	0.81	0.99	0.97	0.96	1
	TSS	0.94	0.81	0.88	0.81	0.78	0.50
	Kappa	0.02	0.002	0.12	0.06	0.09	0.11
	Kappa maximum	0.47	0.41	0.43	0.41	0.39	0.24
	Overall accuracy	0.94	0.81	0.99	0.97	0.96	1
RCP8.5	**10 percentile training presence - Threshold-dependent**	0.05	0.42	0.38	0.37	0.32	0.46
	Sensitivity	1	0.67	0.78	0.77	0.93	1
	Specificity	0.93	0.95	0.99	0.97	0.97	0.99
	TSS	0.93	0.61	0.77	0.74	0.90	0.99
	Kappa	0.02	0.01	0.14	0.07	0.15	0.13
	Kappa maximum	0.46	0.29	0.38	0.37	0.45	0.48
	Overall accuracy	0.93	0.95	0.99	0.97	0.97	0.99

Table 4: Area coverage in percentage under the five defined predicted suitability classes by each tree species

(a). Current						
Suitability	**Abies pindrow**	**Betula utilis**	**Cedrus deodara**	**Picea smithiana**	**Pinus wallichiana**	**Quercus ilex**
0.0-0.2	98.80	84.76	98.32	95.15	94.45	97.82
0.2-0.4	0.87	7.94	0.86	2.68	3.01	1.05
0.4-0.6	0.20	4.32	0.52	1.30	1.63	0.69
0.6-0.7	0.05	1.56	0.16	0.44	0.52	0.26
0.7-1	0.08	1.41	0.13	0.44	0.40	0.18
(b). RCP4.5 Climate-change scenario by 2050						
0.0-0.2	97.61	71.20	97.63	94.50	94.93	98.60
0.2-0.4	1.74	18.77	1.34	3.01	3.14	0.83
0.4-0.6	0.33	8.02	0.62	1.47	1.20	0.33
0.6-0.7	0.11	1.11	0.20	0.51	0.32	0.12
0.7-1	0.20	0.90	0.21	0.52	0.40	0.11
(c). RCP8.5 Climate-change scenario by 2050						
0.0-0.2	99.04	83.71	98.30	94.89	94.63	97.60
0.2-0.4	0.69	10.28	0.90	2.82	3.27	1.26
0.4-0.6	0.14	3.79	0.51	1.34	1.37	0.60
0.6-0.7	0.06	1.43	0.15	0.41	0.36	0.20
0.7-1	0.08	0.78	0.13	0.53	0.37	0.34

Unsuitable (0–0.2): inadmissible natural surroundings;
Less suitable (0.2-0.4): scarcely reasonable living space;
Moderately suitable (0.4-0.6): appropriate territory;
Highly suitable (0.6-0.7): exceptionally appropriate environment and
Very highly suitable (0.7-1.0): profoundly reasonable living space.

6. Discussion

The foremost goal of this study was to present six native trees species (*Abies pindrow*, *Betula utilis, Cedrus deodara, Picea smithiana, Pinus wallichiana* and *Quercus ilex)* current as well as trajectory tree species distribution maps at 1 km spatial resolutions over the entire Gilgit-Baltistan, Pakistan. The ROC-AUC and TSS overall accuracy scores is greater than 0.8. The overall high accuracy with lower uncertainty values of developed tree species maps paved a path towards the suitability of implementation of machine learning open source MaxEnt model in the diverse landscape of Gilgit-Baltistan.

6.1. Tree species distribution modelling studies in Pakistan

From last few years, tens of hundreds of papers were published concealing local to global scales, on methodological and application parts of species distribution modelling (Brotons, 2014; Elith and Leathwick, 2009). The Himalayan region (includes Pakistan) is least explored and reported regarding tree species distribution studies, may be due to the number of factors and reasons, i.e., unavailability of detail forest inventory data, complex forest ecosystem, rough terrain, etc. Over the Himalayan region, Ranjitkar et al. (2014a) conducted a study only considering two tree species, *Rhododendrons* (*R. delavayi* and *R. arboreum*), based on 217 herbarium collections by adopting different ecological niche modelling techniques. While over the same region, Bobrowski et al. (2017) mapped *Betula utilis* tree species based on 590 occurrence points (most of them collected from herbarium) through generalized linear models. Ali et al. (2014) done *Abies pindrow* tree species distribution using HADCM3 A2a global climate change scenario in Swat district, Pakistan. In the *Abies pindrow* tree species distribution study, authors collected and used 23 sample plots at selected different localities within the district.

6.2. Significance of environmental variables in tree species distribution modelling

The performance of trees species distribution models is significantly influenced by the number of species observations, species behaviour, selection of biophysical variables, the ecology and the extent of the study area. Ranjitkar et al. (2014a), Bobrowski et al. (2017) and Ali et al. (2014) computed tree species distribution models by considering bioclimatic variable. Even in this study, only bioclimatic variables were taken. As, temporal medium to coarse spatial resolution satellite images provide plant seasonal phonology in most convenient and cost-effective manner (Leitão and Santos, 2019).

Satellite data can be benefited for species distribution, as it provides information on e.g., ecosystem function, health and structure, complete spatial assessment, and reasonable temporal repeat for the processes that determine geographical distributions (Leitão and Santos, 2019). We can assume and expect better results of species occurrence by integrating satellite-based phenology with bioclimatic variables (Hereford et al., 2017; Leitão and Santos, 2019).

Saatchi et al. (2011) suggested at least 100 samples should be used in the MaxEnt model to ensure best results. Although in this study from the field, not all the 440 tree spices occurrence records were uniformly distributed and counted for distribution modelling of each tree species. Except *Pinus wallichiana* all the species observations were less than 100 (Table 1). Stockwell and Peterson (2002) evaluated predictions from 12 algorithms for 46 species, for the MaxEnt model, they have stated that it had the best predictive power across all sample sizes (Rodríguez-Veiga et al., 2016).

Most of the species distribution-modelling studies use bioclimatic data layers of the WorldClim dataset for the years 1970-2000 (Fick and Hijmans, 2017). While in this study, relatively latest and updated the Chelsa-climate data for the years 1979-2013 were used (Karger et al., 2016). For the RCP4.5 and RCP8.5, climate-change scenarios by 2050 data were also acquired from Chelsa-climate data web portal.

6.3. Forest changes and tree diversity in Gilgit-Baltistan

Based on temporal (1990, 2000 and 2010) Landsat (30m spatial resolution) satellite images Qamar et al. (2011) conducted a study on quantification of deforestation, forest degradation and forest regeneration. In Gilgit-Baltistan, from 1990 to 2010, 7680 ha area deforested, 2701 ha forest degraded while only 2 ha forest regenerated with net change of 10,379 ha. The study also reported -0.31% annual rate of change in forested areas. The forest in Gilgit-Baltistan is very fragmented and exists mostly in patches in the valleys (Ismail et al., 2018; Qamar et al., 2011).

Based on detail forest inventory, Ismail et al. (2018) reported only 9 tree spices in entire the Gilgit-Baltistan, Pakistan. They have collected 556 forest sample plots, 13,135 trees belonging to nine tree species with a total aboveground biomass of 12,887 tonnes with moderate (1.82) Shannon diversity index. For tree species distribution modelling, forest inventory samples of six tree species collected and analysed by Ismail et al. (2018) were utilized in this study. In this research, out of nine we have neglected three species (*Juniperous spp., Pinus gerardiana* and *Taxus baccata*) due to less and limited samples.

6.4. Limitations of this study

The field observation data may have some weakness because it was difficult for the field crews to access the areas with rough terrain, long distances, harsh weather conditions, and locations of forest in steep, narrow valleys. There could be some level of positional uncertainty in the field measurement data, as there is always a potential for human error, especially when inventorying forests in larger areas, and there is always room to improve data collection and processing techniques (Loe et al., 2012). In mountain regions, the resolution of climate data (i.e.1 x1 km) is too coarse for models to distinguish between north- and south-facing slopes. Based on our observations, *Betula utilis* tree species overestimated, although Bobrowski et al. (2017) done *Betula utilis* mapping over Himalaya region, but unfortunately spatial data was not available for statistical comparison.

7. Conclusion

Despite the simplicity in the method, this study sheds new findings on predicting the potential distribution of six native tree species (*Abies pindrow*, *Betula utilis, Cedrus deodara, Picea smithiana, Pinus wallichiana* and *Quercus ilex*) in Gilgit-Baltistan, Pakistan. Our tree species distribution results are from the integrating public domain climatic and topographic datasets with locally collected 450-tree species inventory information. Overall, this study contributes to enlarge tree species distribution research datasets applicability in Pakistan and over the HKH mountains region, may provide interesting insight, which could use for the habitat corridor suitability modelling of endangered species, ground intervention to protect and spread-out tree species distributions. The findings related to utilization of climatic and topographic datasets presented in this research are encouraging but call for additional studies e.g. comparison of different species distribution models, integration of satellite-based season phonological datasets with climatic and topographic information. The possible role of the fusion of microwave and multispectral/hyperspectral datasets can reduce the uncertainty errors in tree species distribution modelling, especially in environments with complex canopy structure and rough topography.

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Annexure

Annex 1: Description of targeted six native tree species (*Abies pindrow*, *Betula utilis, Cedrus deodara, Picea smithiana, Pinus wallichiana* and *Quercus ilex*)

1. ***Abies pindrow*** is a large evergreen tree growing to 40–60 m tall, and with a trunk diameter of up to 2–2.5 m. It has a conical crown with level branches. The shoots are greyish-pink to buff-brown, smooth and glabrous (hairless). Native species of western Himalaya and adjacent mountains: Afghanistan east through northern Pakistan and India to central Nepal. Altitude: 2,400–3,700 m.
2. ***Betula utilis*** is a birch tree native to the Himalayas, growing at elevations up to 4,500 m. It growing as a shrub or tree reaching up to 20 m tall. It frequently grows among scattered conifers, with an undergrowth of shrubs that typically includes evergreen Rhododendron. Flowering occurs from May–July.
3. ***Cedrus deodara*** is a species of cedar native to the western Himalayas in Eastern Afghanistan, Northern Pakistan, India, Southwestern Tibet and Western Nepal, occurring at 1,500–3,200 m altitude. It is a large evergreen coniferous tree reaching 40–50 m tall, exceptionally 60 m with a trunk up to 3 m in diameter.
4. ***Picea smithiana*** is a spruce native to the western Himalaya and adjacent mountains, from northeast Afghanistan, northern Pakistan, India to central Nepal. It grows at altitudes of 2,400-3,600 m in forests together with *Cedrus deodara*, blue pine and Abies pindrow.
5. ***Pinus wallichiana*** is a coniferous tree to 50 m tall with straight trunk and short. Bark on young trees smooth, becoming fissured with age. Seeds production begins at 15-20 years, strongly outbreeding and self-fertilized seed usually grows poorly. Native species of Afghanistan, Bhutan, China, India, Myanmar, Nepal, Pakistan. Altitude: 1500-3600 m, Mean annual temperature: 12-17 deg. C, Mean annual rainfall: 250-2000 mm
6. ***Quercus ilex*** is the most common broadleaf tree in the mid elevation central Himalaya in India. It is a large evergreen oak native to the Mediterranean region. It takes its name from holm, an ancient name for holly. It can grow to 20 m and develop a huge, rounded crown.

Annex 2: Sources of the variables used in MaxEnt algorithm to map six native tree species (*Abies pindrow*, *Betula utilis, Cedrus deodara, Picea smithiana, Pinus wallichiana* and *Quercus ilex*) distribution in Gilgit-Baltistan, Pakistan

	Name of variable	**Source**
1	Bio1 = Annual Mean Temperature	http://chelsa-climate.org/bioclim/
2	Bio2 = Mean Diurnal Range	
3	Bio3 = Isothermality	
4	Bio4 = Temperature Seasonality	
5	Bio5 = Max Temperature of Warmest Month	
6	Bio6 = Min Temperature of Coldest Month	
7	Bio7 = Temperature Annual Range	
8	Bio8 = Mean Temperature of Wettest Quarter	
9	Bio9 = Mean Temperature of Driest Quarter	
10	Bio10 = Mean Temperature of Warmest Quarter	
11	Bio11 = Mean Temperature of Coldest Quarter	
12	Bio12 = Annual Precipitation	
13	Bio13 = Precipitation of Wettest Month	
14	Bio14 = Precipitation of Driest Month	
15	Bio15 = Precipitation Seasonality	
16	Bio16 = Precipitation of Wettest Quarter	
17	Bio17 = Precipitation of Driest Quarter	
18	Bio18 = Precipitation of Warmest Quarter	
19	Bio19 = Precipitation of Coldest Quarter	
20	Aridity = Annual Aridity Index	http://www.cgiar-csi.org/data/global-aridity-and-pet-database
21	PET = Potential Evapo-Transpiration	
22	DEM = Digital Elevation Model	https://earthexplorer.usgs.gov/
23	Terrain Roughness Index	Derived from DEM
24	Slope	Derived from DEM

Annex 3: Pearson’s product-moment correlations among the 24 original variables (21 bioclimatic, and 3 topographic) - Highly correlated variables (r ≥ 0.9) shown in red boldface excluded in the MaxEnt model for six native tree species (*Abies pindrow*, *Betula utilis, Cedrus deodara, Picea smithiana, Pinus wallichiana* and *Quercus ilex*) distribution in Gilgit-Baltistan, Pakistan

1. *Abies pindrow*

	Aridity	DEM	PET	TRI	Slope	Bio1	Bio2	Bio3	Bio4	Bio5	Bio6	Bio7	Bio8	Bio9	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19
Aridity	1																							
DEM	-0.63	1																						
PET	0.07	-0.79	1																					
TRI	-0.5	0.33	-0.14	1																				
Slope	-0.37	0.42	-0.17	0.1	1																			
Bio1	0.77	-0.93	0.66	-0.45	-0.34	1																		
Bio2	0.67	-0.36	-0.13	-0.17	-0.3	0.39	1																	
Bio3	0.77	-0.84	0.47	-0.28	-0.36	0.85	0.75	1																
Bio4	-0.82	0.9	-0.56	0.38	0.35	-0.95	-0.56	-0.96	1															
Bio5	0.44	-0.85	0.84	-0.43	-0.24	0.89	-0.03	0.57	-0.72	1														
Bio6	0.25	-0.75	0.87	-0.3	-0.15	0.76	-0.27	0.41	-0.61	0.95	1													
Bio7	0.03	0.51	-0.78	0.1	0.01	-0.49	0.55	-0.14	0.36	-0.74	-0.91	1												
Bio8	-0.53	-0.04	0.53	0.04	0.23	-0.01	-0.75	-0.41	0.27	0.42	0.53	-0.59	1											
Bio9	0.82	-0.92	0.59	-0.46	-0.36	0.99	0.47	0.88	-0.96	0.84	0.69	-0.4	-0.1	1										
Bio10	0.71	-0.92	0.7	-0.48	-0.33	0.99	0.27	0.77	-0.89	0.94	0.83	-0.56	0.11	0.97	1									
Bio11	0.78	-0.93	0.65	-0.46	-0.35	1	0.39	0.86	-0.96	0.88	0.76	-0.49	-0.05	0.99	0.98	1								
Bio12	0.8	-0.21	-0.29	-0.48	-0.24	0.42	0.33	0.29	-0.4	0.2	0.06	0.13	-0.43	0.47	0.41	0.43	1							
Bio13	0.65	-0.03	-0.42	-0.41	-0.19	0.25	0.32	0.14	-0.21	0.05	-0.1	0.29	-0.42	0.3	0.24	0.25	0.95	1						
Bio14	0.64	0.06	-0.54	-0.34	-0.15	0.15	0.37	0.1	-0.15	-0.09	-0.24	0.41	-0.51	0.22	0.13	0.16	0.93	0.97	1					
Bio15	-0.4	0.46	-0.36	0.27	0.08	-0.49	0.22	-0.25	0.47	-0.49	-0.59	0.65	-0.1	-0.46	-0.5	-0.51	-0.29	-0.01	0.01	1				
Bio16	0.66	-0.03	-0.42	-0.41	-0.2	0.25	0.34	0.15	-0.21	0.05	-0.11	0.3	-0.42	0.31	0.24	0.25	0.96	1	0.98	-0.01	1			
Bio17	0.61	0.08	-0.53	-0.35	-0.13	0.13	0.28	0.04	-0.11	-0.07	-0.21	0.36	-0.43	0.2	0.12	0.14	0.94	0.98	0.99	-0.02	0.98	1		
Bio18	0.66	-0.41	0.12	-0.44	-0.2	0.56	-0.06	0.27	-0.5	0.49	0.5	-0.43	-0.08	0.56	0.58	0.58	0.78	0.61	0.54	-0.78	0.6	0.58	1	
Bio19	0.87	-0.24	-0.35	-0.43	-0.29	0.42	0.67	0.48	-0.48	0.08	-0.13	0.39	-0.67	0.5	0.36	0.43	0.91	0.89	0.91	-0.05	0.9	0.88	0.52	1

2. *Betula utilis*

	Aridity	DEM	PET	TRI	Slope	Bio1	Bio2	Bio3	Bio4	Bio5	Bio6	Bio7	Bio8	Bio9	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19
Aridity	1																							
DEM	-0.11	1																						
PET	-0.58	-0.72	1																					
TRI	-0.75	0.09	0.36	1																				
Slope	-0.7	0.05	0.47	0.59	1																			
Bio1	0.71	-0.72	0.13	-0.67	-0.39	1																		
Bio2	0.96	-0.07	-0.62	-0.63	-0.63	0.63	1																	
Bio3	0.61	-0.75	0.17	-0.42	-0.24	0.89	0.64	1																
Bio4	-0.64	0.77	-0.19	0.5	0.29	-0.94	-0.61	-0.98	1															
Bio5	0.46	-0.82	0.42	-0.55	-0.24	0.93	0.34	0.77	-0.85	1														
Bio6	0.13	-0.91	0.71	-0.29	0.03	0.78	0.02	0.69	-0.76	0.93	1													
Bio7	0.63	0.63	-0.97	-0.4	-0.57	-0.05	0.67	-0.15	0.17	-0.32	-0.64	1												
Bio8	0.07	-0.51	0.47	-0.39	0.12	0.59	-0.02	0.4	-0.45	0.71	0.73	-0.41	1											
Bio9	0.79	-0.64	0.02	-0.71	-0.45	0.99	0.72	0.89	-0.93	0.89	0.7	0.06	0.54	1										
Bio10	0.69	-0.72	0.16	-0.68	-0.4	0.99	0.6	0.85	-0.91	0.96	0.8	-0.06	0.62	0.98	1									
Bio11	0.71	-0.73	0.14	-0.65	-0.39	1	0.63	0.9	-0.95	0.94	0.78	-0.07	0.57	0.99	0.99	1								
Bio12	0.98	0.03	-0.7	-0.65	-0.66	0.58	0.96	0.52	-0.54	0.3	-0.03	0.72	-0.1	0.67	0.55	0.58	1							
Bio13	0.97	0	-0.66	-0.63	-0.63	0.6	0.95	0.53	-0.56	0.33	0	0.7	-0.08	0.68	0.58	0.6	1	1						
Bio14	0.96	0.05	-0.71	-0.64	-0.61	0.57	0.96	0.51	-0.52	0.29	-0.05	0.73	-0.08	0.66	0.54	0.57	0.99	0.99	1					
Bio15	0.22	-0.58	0.4	-0.16	0.13	0.62	0.18	0.57	-0.59	0.72	0.7	-0.32	0.53	0.57	0.65	0.63	0.15	0.22	0.18	1				
Bio16	0.98	0.02	-0.68	-0.65	-0.64	0.6	0.95	0.52	-0.55	0.32	-0.01	0.71	-0.07	0.68	0.57	0.6	1	1	1	0.2	1			
Bio17	0.97	0.04	-0.7	-0.65	-0.62	0.58	0.95	0.51	-0.53	0.3	-0.03	0.73	-0.07	0.67	0.55	0.58	1	1	1	0.19	1	1		
Bio18	0.92	0.06	-0.71	-0.55	-0.7	0.47	0.9	0.43	-0.46	0.19	-0.12	0.73	-0.27	0.56	0.44	0.48	0.97	0.96	0.94	0.01	0.96	0.95	1	
Bio19	0.98	0.01	-0.69	-0.66	-0.64	0.6	0.98	0.55	-0.56	0.31	-0.02	0.72	-0.07	0.69	0.57	0.6	1	0.99	1	0.16	0.99	1	0.94	1

3. *Cedrus deodara*

	Aridity	DEM	PET	TRI	Slope	Bio1	Bio2	Bio3	Bio4	Bio5	Bio6	Bio7	Bio8	Bio9	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19
Aridity	1																							
DEM	0.25	1																						
PET	-0.54	-0.91	1																					
TRI	-0.36	-0.32	0.39	1																				
Slope	0.13	0.36	-0.25	0.01	1																			
Bio1	0.09	-0.83	0.77	0.19	-0.1	1																		
Bio2	-0.3	0.3	-0.26	-0.21	-0.29	-0.61	1																	
Bio3	-0.56	-0.8	0.95	0.4	-0.14	0.75	-0.27	1																
Bio4	0.32	0.86	-0.94	-0.35	0.13	-0.91	0.46	-0.96	1															
Bio5	-0.04	-0.86	0.84	0.23	-0.11	0.99	-0.58	0.82	-0.95	1														
Bio6	-0.2	-0.84	0.88	0.33	-0.06	0.94	-0.62	0.9	-0.98	0.97	1													
Bio7	0.34	0.77	-0.89	-0.41	0.01	-0.86	0.62	-0.92	0.96	-0.9	-0.98	1												
Bio8	0	-0.21	0.21	-0.02	0	0.27	-0.3	0.2	-0.25	0.28	0.29	-0.28	1											
Bio9	0.16	-0.82	0.73	0.16	-0.11	1	-0.61	0.7	-0.87	0.98	0.91	-0.81	0.27	1										
Bio10	0.14	-0.82	0.74	0.17	-0.09	1	-0.63	0.72	-0.88	0.98	0.93	-0.83	0.28	1	1									
Bio11	-0.01	-0.85	0.83	0.24	-0.1	0.99	-0.6	0.82	-0.95	1	0.97	-0.91	0.28	0.98	0.99	1								
Bio12	0.89	0.26	-0.51	-0.33	0.2	0.05	-0.43	-0.57	0.33	-0.07	-0.19	0.3	0	0.11	0.09	-0.05	1							
Bio13	0.85	0.21	-0.47	-0.31	0.15	0.06	-0.39	-0.54	0.31	-0.05	-0.18	0.29	-0.08	0.12	0.1	-0.03	0.97	1						
Bio14	0.88	0.13	-0.4	-0.27	0.17	0.17	-0.46	-0.46	0.21	0.06	-0.07	0.19	-0.09	0.23	0.21	0.08	0.96	0.98	1					
Bio15	-0.4	-0.16	0.18	0	-0.26	-0.13	0.25	0.1	-0.01	-0.08	-0.05	0.02	0.14	-0.14	-0.14	-0.1	-0.28	-0.13	-0.23	1				
Bio16	0.86	0.19	-0.46	-0.32	0.15	0.08	-0.4	-0.53	0.29	-0.04	-0.16	0.28	-0.04	0.14	0.12	-0.02	0.98	1	0.98	-0.12	1			
Bio17	0.88	0.15	-0.41	-0.28	0.16	0.16	-0.45	-0.47	0.23	0.04	-0.09	0.21	-0.09	0.22	0.19	0.06	0.97	0.99	1	-0.22	0.99	1		
Bio18	0.64	0.44	-0.56	-0.32	0.31	-0.16	-0.36	-0.59	0.42	-0.24	-0.3	0.34	0.22	-0.12	-0.13	-0.22	0.8	0.66	0.63	-0.49	0.66	0.63	1	
Bio19	0.92	0.13	-0.42	-0.32	0.12	0.16	-0.41	-0.48	0.23	0.04	-0.1	0.24	-0.08	0.23	0.21	0.06	0.97	0.98	0.99	-0.23	0.98	0.99	0.63	1

4. *Picea smithiana*

	Aridity	DEM	PET	TRI	Slope	Bio1	Bio2	Bio3	Bio4	Bio5	Bio6	Bio7	Bio8	Bio9	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19
Aridity	1																							
DEM	0.06	1																						
PET	-0.26	-0.94	1																					
TRI	-0.35	-0.11	0.18	1																				
Slope	-0.16	0.24	-0.14	0.44	1																			
Bio1	0.42	-0.78	0.72	-0.01	-0.13	1																		
Bio2	-0.36	0.31	-0.34	0.17	0.13	-0.46	1																	
Bio3	-0.49	-0.53	0.6	0.32	0.19	0.39	0.35	1																
Bio4	0.13	0.8	-0.85	-0.2	-0.07	-0.81	0.22	-0.81	1															
Bio5	0.52	-0.72	0.66	-0.07	-0.19	0.96	-0.61	0.16	-0.67	1														
Bio6	0.32	-0.77	0.76	-0.01	-0.12	0.94	-0.7	0.29	-0.79	0.95	1													
Bio7	0.02	0.7	-0.78	-0.07	-0.02	-0.74	0.71	-0.42	0.82	-0.71	-0.89	1												
Bio8	0.24	-0.63	0.6	0.01	-0.11	0.76	-0.41	0.36	-0.68	0.72	0.75	-0.67	1											
Bio9	0.45	-0.76	0.69	-0.01	-0.13	1	-0.4	0.4	-0.8	0.95	0.91	-0.69	0.75	1										
Bio10	0.55	-0.71	0.63	-0.07	-0.18	0.98	-0.54	0.21	-0.69	0.99	0.93	-0.68	0.73	0.97	1									
Bio11	0.41	-0.78	0.73	-0.01	-0.12	1	-0.5	0.38	-0.82	0.97	0.96	-0.78	0.77	0.99	0.98	1								
Bio12	0.9	0.06	-0.22	-0.35	-0.08	0.41	-0.48	-0.39	0.02	0.48	0.38	-0.17	0.3	0.42	0.51	0.41	1							
Bio13	0.88	0.12	-0.29	-0.34	-0.06	0.34	-0.36	-0.38	0.08	0.41	0.29	-0.06	0.21	0.36	0.45	0.34	0.98	1						
Bio14	0.85	0.19	-0.37	-0.32	-0.04	0.27	-0.2	-0.32	0.1	0.31	0.18	0.04	0.16	0.3	0.36	0.27	0.94	0.98	1					
Bio15	0.03	0.12	-0.2	-0.06	0.1	-0.09	0.58	0.23	0.05	-0.15	-0.27	0.39	-0.1	-0.05	-0.11	-0.11	0.05	0.22	0.29	1				
Bio16	0.89	0.11	-0.28	-0.34	-0.06	0.35	-0.33	-0.36	0.06	0.41	0.29	-0.05	0.23	0.37	0.46	0.35	0.98	1	0.98	0.23	1			
Bio17	0.86	0.17	-0.34	-0.33	-0.05	0.29	-0.26	-0.34	0.1	0.34	0.21	0.01	0.18	0.32	0.39	0.29	0.96	0.99	1	0.26	0.99	1		
Bio18	0.71	-0.09	0.01	-0.29	-0.08	0.45	-0.81	-0.43	-0.08	0.56	0.56	-0.46	0.42	0.43	0.54	0.47	0.83	0.71	0.61	-0.42	0.7	0.65	1	
Bio19	0.85	0.19	-0.38	-0.33	-0.05	0.26	-0.09	-0.28	0.11	0.28	0.13	0.12	0.15	0.3	0.35	0.25	0.91	0.95	0.99	0.35	0.96	0.98	0.54	1

5. *Pinus wallichiana*

	Aridity	DEM	PET	TRI	Slope	Bio1	Bio2	Bio3	Bio4	Bio5	Bio6	Bio7	Bio8	Bio9	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19
Aridity	1																							
DEM	-0.3	1																						
PET	0.01	-0.94	1																					
TRI	-0.25	-0.03	0.08	1																				
Slope	-0.26	0.17	-0.09	0.28	1																			
Bio1	0.52	-0.93	0.83	-0.06	-0.15	1																		
Bio2	0.51	0.02	-0.24	-0.27	-0.17	0.08	1																	
Bio3	0.25	-0.67	0.63	0.08	-0.17	0.7	0.11	1																
Bio4	-0.27	0.65	-0.63	-0.11	0.13	-0.7	0.2	-0.91	1															
Bio5	0.44	-0.9	0.83	-0.08	-0.14	0.93	0.1	0.46	-0.43	1														
Bio6	0.29	-0.95	0.93	0.03	-0.12	0.95	-0.16	0.65	-0.68	0.93	1													
Bio7	0.17	0.54	-0.66	-0.25	0.01	-0.49	0.63	-0.7	0.86	-0.29	-0.62	1												
Bio8	0.24	-0.81	0.76	-0.07	-0.01	0.78	0.18	0.29	-0.17	0.92	0.79	-0.09	1											
Bio9	0.05	-0.01	0.04	0.13	0.06	0.08	-0.44	0.35	-0.6	-0.21	0.06	-0.59	-0.42	1										
Bio10	0.54	-0.92	0.81	-0.09	-0.15	0.99	0.11	0.58	-0.58	0.98	0.94	-0.38	0.85	-0.04	1									
Bio11	0.51	-0.92	0.83	-0.03	-0.16	0.99	0.02	0.75	-0.77	0.9	0.95	-0.57	0.71	0.16	0.96	1								
Bio12	0.59	0.17	-0.34	0.05	0.03	0.03	0.03	-0.03	-0.18	-0.14	-0.13	0.04	-0.33	0.55	0	0.07	1							
Bio13	0.59	0.13	-0.3	0.08	0.05	0.06	0.04	-0.09	-0.11	-0.05	-0.08	0.09	-0.23	0.44	0.06	0.09	0.98	1						
Bio14	0.41	0.32	-0.45	0.1	0.12	-0.13	-0.03	-0.05	-0.16	-0.34	-0.28	0.01	-0.5	0.61	-0.18	-0.09	0.96	0.92	1					
Bio15	0.15	-0.04	0.03	0.05	0.02	0.11	-0.02	0.13	-0.18	0.08	0.11	-0.12	-0.05	0.23	0.11	0.14	0.38	0.5	0.38	1				
Bio16	0.6	0.14	-0.31	0.06	0.05	0.07	0.06	-0.07	-0.12	-0.06	-0.09	0.1	-0.24	0.46	0.06	0.09	0.98	1	0.93	0.47	1			
Bio17	0.45	0.28	-0.41	0.09	0.12	-0.09	-0.03	-0.06	-0.15	-0.28	-0.23	0.02	-0.45	0.59	-0.13	-0.05	0.97	0.94	1	0.4	0.95	1		
Bio18	0.77	-0.1	-0.11	0.03	-0.11	0.28	0.09	-0.04	-0.13	0.22	0.14	0.1	0.04	0.2	0.3	0.29	0.75	0.74	0.58	-0.03	0.74	0.62	1	
Bio19	0.42	0.32	-0.45	0.07	0.06	-0.13	0	0.02	-0.21	-0.37	-0.29	-0.02	-0.55	0.68	-0.2	-0.08	0.95	0.88	0.98	0.36	0.9	0.97	0.56	1

6. Quercus_ilex

	Aridity	DEM	PET	TRI	Slope	Bio1	Bio2	Bio3	Bio4	Bio5	Bio6	Bio7	Bio8	Bio9	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19
Aridity	1																							
DEM	0.25	1																						
PET	-0.35	-0.99	1																					
TRI	0.37	0.45	-0.51	1																				
Slope	0.42	0	-0.04	0.36	1																			
Bio1	-0.07	-0.97	0.95	-0.43	0.12	1																		
Bio2	-0.07	0.76	-0.75	0.11	-0.28	-0.84	1																	
Bio3	-0.3	-0.97	0.99	-0.52	0.02	0.97	-0.75	1																
Bio4	0.23	0.98	-0.99	0.49	-0.05	-0.99	0.8	-0.99	1															
Bio5	-0.09	-0.97	0.96	-0.44	0.11	1	-0.85	0.97	-0.99	1														
Bio6	-0.16	-0.97	0.97	-0.43	0.1	0.99	-0.87	0.98	-0.99	1	1													
Bio7	0.21	0.96	-0.97	0.42	-0.1	-0.98	0.88	-0.98	0.99	-0.98	-1	1												
Bio8	-0.04	-0.42	0.35	0.16	0.17	0.35	-0.42	0.32	-0.34	0.36	0.36	-0.37	1											
Bio9	-0.05	-0.96	0.95	-0.44	0.11	1	-0.83	0.96	-0.98	1	0.99	-0.97	0.35	1										
Bio10	-0.03	-0.96	0.94	-0.41	0.14	1	-0.85	0.95	-0.98	1	0.99	-0.97	0.36	1	1									
Bio11	-0.1	-0.97	0.96	-0.44	0.1	1	-0.84	0.97	-0.99	1	1	-0.98	0.35	1	1	1								
Bio12	0.81	0.01	-0.08	0.4	0.48	0.17	-0.49	-0.05	-0.03	0.16	0.14	-0.11	0.12	0.17	0.21	0.15	1							
Bio13	0.77	0.11	-0.17	0.38	0.4	0.06	-0.4	-0.15	0.08	0.05	0.03	-0.02	0	0.06	0.1	0.04	0.97	1						
Bio14	0.72	-0.02	-0.04	0.28	0.38	0.19	-0.5	-0.02	-0.06	0.18	0.16	-0.15	-0.04	0.19	0.23	0.17	0.95	0.98	1					
Bio15	0.12	0.41	-0.38	0.4	0.27	-0.33	-0.01	-0.31	0.33	-0.32	-0.28	0.23	0.16	-0.35	-0.33	-0.32	0.38	0.41	0.28	1				
Bio16	0.77	0.07	-0.14	0.39	0.43	0.1	-0.44	-0.11	0.04	0.09	0.07	-0.06	0.06	0.1	0.14	0.08	0.98	1	0.97	0.43	1			
Bio17	0.74	-0.01	-0.05	0.29	0.37	0.18	-0.48	-0.04	-0.04	0.16	0.14	-0.13	-0.04	0.17	0.21	0.15	0.95	0.98	1	0.27	0.97	1		
Bio18	0.54	0.04	-0.13	0.51	0.39	0.03	-0.3	-0.12	0.06	0.03	0.01	0	0.64	0.03	0.06	0.02	0.6	0.45	0.34	0.39	0.5	0.35	1	
Bio19	0.81	-0.02	-0.05	0.3	0.42	0.2	-0.47	-0.02	-0.06	0.19	0.16	-0.13	-0.04	0.2	0.24	0.17	0.97	0.97	0.98	0.24	0.97	0.98	0.4	1

Annex 4: Pearson's product-moment correlations among the 24 original variables (21 bioclimatic, and 3 topographic) – All the highly correlated variables (r ≥ 0.9) shown in red boldface excluded in the MaxEnt model and red boldface yellow highlighted are the common parameters among six native tree species (*Abies pindrow*, *Betula utilis, Cedrus deodara, Picea smithiana, Pinus wallichiana* and *Quercus ilex*)

Abies pindrow	***Betula utilis***	***Cedrus deodara***	***Picea smithiana***	***Pinus wallichiana***	***Quercus ilex***
Aridity	**Aridity**	Aridity	Aridity	Aridity	Aridity
DEM	DEM	DEM	DEM	**DEM**	DEM
PET	**PET**	**PET**	**PET**	**PET**	**PET**
TRI	TRI	TRI	TRI	TRI	TRI
Slope	Slope	Slope	Slope	Slope	Slope
Bio1	**Bio1**	**Bio1**	**Bio1**	**Bio1**	**Bio1**
Bio2	Bio2	Bio2	Bio2	Bio2	**Bio2**
Bio3	Bio3	**Bio3**	Bio3	Bio3	**Bio3**
Bio4	**Bio4**	**Bio4**	**Bio4**	**Bio4**	**Bio4**
Bio5	**Bio5**	**Bio5**	**Bio5**	**Bio5**	**Bio5**
Bio6	**Bio6**	**Bio6**	**Bio6**	**Bio6**	**Bio6**
Bio7	Bio7	**Bio7**	Bio7	Bio7	**Bio7**
Bio8	Bio8	Bio8	Bio8	Bio8	Bio8
Bio9	**Bio9**	**Bio9**	**Bio9**	Bio9	**Bio9**
Bio10	**Bio10**	**Bio10**	**Bio10**	**Bio10**	**Bio10**
Bio11	**Bio11**	**Bio11**	**Bio11**	**Bio11**	**Bio11**
Bio12	**Bio12**	**Bio12**	**Bio12**	**Bio12**	**Bio12**
Bio13	**Bio13**	**Bio13**	**Bio13**	**Bio13**	**Bio13**
Bio14	**Bio14**	**Bio14**	**Bio14**	**Bio14**	**Bio14**
Bio15	Bio15	Bio15	Bio15	Bio15	Bio15
Bio16	**Bio16**	**Bio16**	**Bio16**	**Bio16**	**Bio16**
Bio17	**Bio17**	**Bio17**	**Bio17**	**Bio17**	**Bio17**
Bio18	**Bio18**	Bio18	**Bio18**	Bio18	Bio18
Bio19	**Bio19**	**Bio19**	**Bio19**	**Bio19**	**Bio19**